7TH ESTAD

PROCEEDINGS

DIGITAL TRANSFORMATION

VERONA, ITALY

6-9 OCTOBER 2025

Palaexpo Veronafiere

ASSOCIAZIONE ITALIANA DI METALLURGIA

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ABOUT 7th ESTAD 2025

The European Steel Technology and Application Days – ESTAD took place for the seventh time after Paris 2014, Düsseldorf 2015, Vienna 2017, Düsseldorf 2019, Stockholm 2021 and Düsseldorf 2023.

7th ESTAD 2025 was hosted by AIM, the Italian Association for Metallurgy, in cooperation with Siderweb – the Italian steel community, in Verona – Italy on 6-9 October 2025.
ESTAD was founded ten years ago with the aim of creating a flagship conference bringing together steel manufacturers, suppliers, users, universities, research institutes and plant engineers and has become a leading conference for metallurgy and materials technology.

The meeting focused on the technological advances, changes of the supply chain involving the raw materials and energy sources, transformation of the production processes and plants to accomplish the twin transition (ecological and digital) and the new perspective of steel applications.

7TH ESTAD

7TH EUROPEAN STEEL TECHNOLOGY AND APPLICATION DAYS

VERONA, ITALY

6-9 OCTOBER 2025

Published in Italy
ISBN 9788898990436
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Associazione Italiana di Metallurgia

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ASSOCIAZIONE ITALIANA DI METALLURGIA
I – 20121 Milano
Via Filippo Turati, 8
Tel. +39-02-76397770 / +39-0276021132
e-mail: aim@aimnet.it
www.aimnet.it

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DIGITAL TRANSFORMATION

From Data to Benefit - Application of AI Technologies in Steel Production

D. Bettinger, K. Herzog, P. Krahwinkler, Primetals Technologies, Austria
A. Thekale, Primetals Technologies, Germany

In the ongoing digital transformation of the steel industry, Artificial Intelligence is increasingly integrated into the automation of the production processes. However, the true potential of AI technologies can only be realized if preconditions to data quality are given, and domain expertise is effectively digitized.
This paper explores the application of AI technologies – such as machine learning, deep learning, and expert systems – in areas like predictive maintenance, process control, and defect detection.

A special focus is placed on the unique characteristics of steel production data, including its complexity, heterogeneity, and real-time processing requirements. Additionally, we discuss the importance of capturing and structuring expert knowledge in digital form to enhance AI-driven decision-making and ensure long-term knowledge retention.

By combining high-quality data with digitized know-how, steel manufacturers can achieve tangible benefits such as reduced downtime, improved product quality, enhanced sustainability, and continuous improvement of the production processes along the entire production chain. This paper will highlight best practices for transforming raw data and human expertise into actionable insights, demonstrating how AI can drive measurable benefits in steel production automation.

KEYWORDS: AI – MACHINE LEARNING – BIG DATA – KNOW HOW – PLANT AUTOMATION – AUTONOMOUS PLANT OPERATION – HYBRID MODEL

INTRODUCTION

Automation is fundamental in metals production for a long time now. Smart algorithms within the automation can make the difference if one aims at producing modern and high-class product mixes. The fast development and evolution of AI technologies opens up the possibility to further enhance existing automation algorithms, and even to develop completely new functionalities that bring automation to the next level.
To use AI-based technologies in control systems within the automation in a steel production environment, several technical, operational, and organizational requirements must be met to ensure that AI technologies can function reliably, safely, and effectively in such a complex and high-stakes industrial setting.

'AI' as a broad term, is covering all efforts aiming to replicate and extend human capabilities for intelligence and reasoning in machines [1].
Looking at the human capabilities necessary to operate complex plants in steel production, we can see mainly three groups of capabilities:

1.) The capability to interpret data or to extract information out of available data
2.) The capability to make decisions based on interpreted data relevant know-how
3.) The capability to act or execute decisions

Especially in the group (1) and (2), data-driven methods can be widely applied, whereas "acting", meaning executing decisions, is mainly a task of "traditional" automation and robotics.

Defining how beneficial or effective the usage of data in process control is, we can define

Effectiveness of Data* = *Quality of Data* x *Quality of Applied Know-how* x *Degree of Implementation

Looking at the capability to interpret data or extract information out of data, models are widely used. Models allow us on the one hand to provide information about characteristics that are not measurable, e.g., process parameters from the inside of a blast furnace and on the other hand prediction of process parameters. In the past models were mainly first principle models, AI technologies allow us to create data-based, machine-learning (ML) models.
First-principle models are grounded in the fundamental laws of science, such as physics, chemistry, or thermodynamics. They are highly interpretable, typically require less empirical data to build, but they demand significant domain expertise and time to develop. They are particularly reliable when extrapolating beyond observed data, provided the underlying assumptions remain valid.
In contrast, **machine learning models** are data-driven and do not rely on explicit knowledge of the system's internal workings. Instead, they learn patterns and relationships directly from data. This makes them especially powerful for modelling complex or poorly understood systems where first-principle formulations are difficult or impossible to derive. However, machine learning models often require large volumes of high-quality data to perform well. They tend to be less interpretable, especially in the case of deep learning models, which can act as "black boxes." While they are generally faster to develop when data is available, they may struggle to generalize or extrapolate beyond the data they were trained on.
Black-box behavior, hallucination and unpredictable behavior due to poor training data are absolutely unwanted when applied in control systems in a production environment.

Assuming that ML-models provide reliable information, applying know-how leads to proper decisions. This know-how in the past was in the operators brains, gained from training and experience. In a similar way, a digital knowledge-base can be built using AI technologies.
The most commonly use technology are expert systems, formalizing domain-specific knowledge into rules and logic, enabling consistent and explainable decisions. Consistent decisions per se are not necessarily good decisions but they are the foundation for continuous improvement and machine-learning technologies can be applied to permanently improve the ruleset (= digital knowledge base). Having explainable decisions is an important factor for the acceptance of AI-based systems.

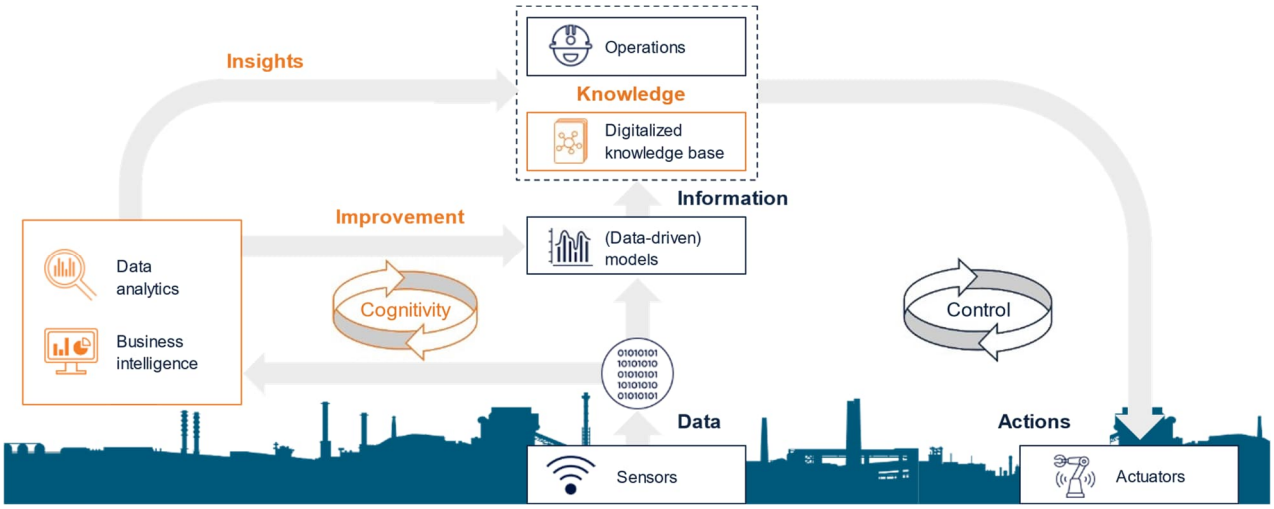

Figure 1: Application of AI technologies to control and continuously improve production processes Right branch: Control - plant able to make decisions and take actions; Left branch: Cognitivity - plant is continuously adapting and improving.

If the quality of data used for training of models and deriving know-how for the digital knowledge base, decisions can be automated and automatically executed without human-in-the-loop, following the idea of autonomous plant operation [2].

DATA QUALITY

Figure 2: Data quality is the foundation of all data-driven applications

Correct Training Data

Correct training data is essential for the accuracy and reliability of predictive models. Using incorrect or biased training data can lead to flawed predictions and decisions. Ensuring the quality of training data involves rigorous validation and continuous monitoring. This process includes checking for data accuracy, completeness, and relevance to the specific use case. Additionally, it is important to regularly update the training data to reflect any changes in the underlying processes or conditions.

Cope with Changed Modes of Operation / Boundary Conditions

Adapting to changes in operational modes and boundary conditions is crucial for maintaining model performance. Continuous monitoring and adjustment of data inputs is necessary to cope with these changes. This ensures that models remain relevant and accurate over time. There are various strategies for identifying and responding to changes in boundary conditions, such as implementing adaptive algorithms and incorporating feedback loops. These strategies help in maintaining the robustness and reliability of predictive models.

Balanced Training Data Sets

Balanced training data sets are vital to avoid overfitting and ensure generalizability. Imbalanced data can skew model outcomes and leading to inaccurate predictions. Techniques such as oversampling, undersampling, and synthetic data generation can help balance training data. Imbalanced data can affect model performance and practical solutions for achieving balanced data sets are required. It is also important to continuously evaluate and adjust the updated training data to maintain balance.

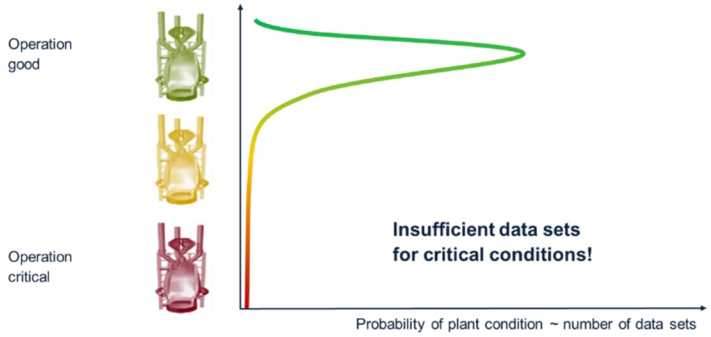

Figure 3: Un-balanced training data sets are common in the iron & steel industry

Re-calibration of Input-Data

Re-calibration of input data is a crucial step in maintaining data quality. Periodic re-calibration aligns data with current operational conditions, improving model accuracy. This process involves adjusting data inputs to reflect changes in the environment or system. There are various methods for re-calibrating input data, such as using statistical techniques and machine learning algorithms. The benefits of re-calibration include improved model performance and reduced prediction errors.

Downscale Data to Minimal Sampling Frequency

Downscaling data to minimal sampling frequency can minimize noise and enhance data quality. Reducing the frequency of data collection helps in focusing on the most relevant data points. This approach ensures that the data used for analysis is of high quality and free from unnecessary noise. However, there are trade-offs between data frequency and quality, and guidelines for determining the optimal sampling frequency are required.

Extrapolation Beyond the Training Data Range

Extrapolation beyond the training data range poses significant risks to prediction reliability. Such extrapolation can lead to unreliable predictions and flawed decisions. It is essential to establish boundaries for data extrapolation and use techniques to mitigate these risks. The potential pitfalls of extrapolation require strategies for managing these risks, such as using robust statistical methods and incorporating domain knowledge.

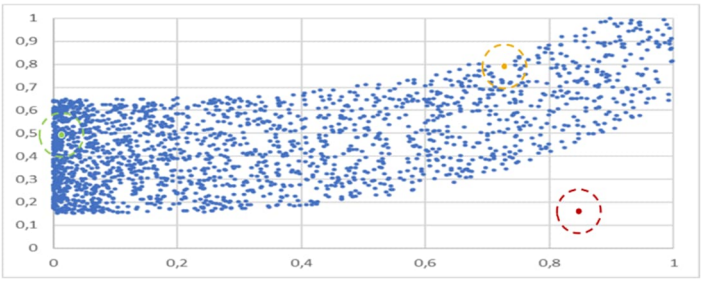

Figure 4: Trust range: Result based on experience or extrapolation?

DIGITALIZATION OF KNOW-HOW

Sensors generate data, describing the process conditions and the production in a standard automation system. To extract meaningful information from this data, models are used – either conventional first-principles models or data-driven models. This information is then provided to operators or decision support systems, who can decide on the appropriate control and optimization actions. These actions are executed by actuators, thereby influencing process conditions and production.

Modern automation systems offer a digitalized knowledge base, allowing the system to take autonomous actions without human intervention. Data can be used for more purposes than just control actions; it can also improve the control system through cognitive features like attention, perception, and memory.

Human insights and self-learning – the dynamic duo of cognitive systems
Cognitivity, in terms of automation systems, is the ability to learn, understand and build knowledge, and can be divided into two areas: Automatic self-learning improvements that can happen continuously on the one hand side, and human insights that are manually implemented and digitalized into the automation system occasionally on the other hand.

Machine learning or self-learning algorithms can be applied to improve models. However, self-learning functionality comes with risks, such as data quality challenges and black-box behavior, including coincidental learning and confusing correlation with causality. Reliable and robust results are typically achieved by restricting models to specific parts of the process. Global attempts, like generating a digital twin of the entire process, often fail, especially in critical operational situations that rarely occur. Since data-driven models like machine learning models require past similar situations for training, rare situations are not represented in the training data.
While machine learning applications often provide excellent precision when interpolating, extrapolation to new, unseen situations tends to be unreliable. Even worse, an extensive deterioration of reliability can occur without warning. This contrasts with classical models, where model assumptions typically indicate the validity range.
Therefore, it is important to use a suitable combination of classical, first principles models and AI.

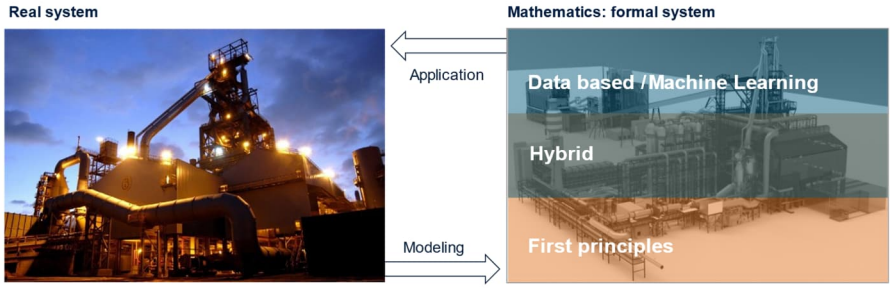

Figure 5: Modeling: Different modeling approaches Hybrid models combine the benefits of first principles models and Data based models, in terms of reliability, performance, validity range and transparency

Hybrid approaches are particularly valuable for defining rules and operational practices. Implementing self-learning functionality is delicate in decision-making for critical processes, such as those in iron- and steelmaking plants.
Preferably, new insights are gained by analyzing data with various data analytics or business intelligence methods. These insights are then transferred into digitalized knowledge by being manually entered into the digital knowledge base, involving the "human in the loop".

TAKING ACTION
The third ingredient to maximize the effectiveness of data is the Degree of Implementation: Once you have collected the data, extracted the relevant information, built a knowledge base, and developed a method to systematically enhance and digitalize your knowledge, it is important to ensure that this is used to control and optimize the process. Following the principle that "data, information, and knowledge without action are useless."

USE-CASES
In the following, we describe the mentioned principles above on three different use cases. They show the clear potential and the benefits of applying AI to the steelmaking process. But the same is true in other steps of the metals production process steps such as rolling.

Ironmaking Product Quality Prediction with hybrid Machine Learning Models
Quality predictions for final or intermediate products allow for immediate adjustments to process parameters to stabilize the process – rather than waiting several hours for lab results. Using these predictions the process conditions and product quality can be stabilized.
We have developed applications tailored for various ironmaking facilities. These include sinter permeability curves based on moisture content, monitoring of product quality in sintering operations, prediction of hot metal temperature and silicon content in blast furnaces, and assessment of product quality—product temperature, degree of metallization, and carbon content—in the direct reduction process.

We achieved the best results using a hybrid approach, combining a prediction based on first principles and technologically engineered features with a combination of AI models. The question of trust is important, when predictions are used to control the process conditions and transparency is a necessary condition for trust as described in [3]. To reduce the black box problem and increase reliability, we used a transparency approach as described in [4]. The methods used help interpreting the results and understand the influencing factors on the prediction and therefore provide valuable meta-data for the decision-making chain of a critical process as the ironmaking processes.

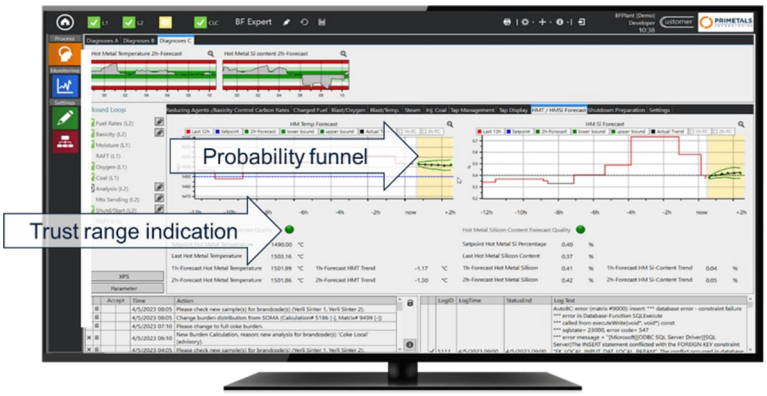

Figure 6: Hot Metal Temperature and Si Prediction integrated into XPS

Closed-loop process optimization with Expert Systems
The VAiron BF Expert System leverages a comprehensive knowledge base that reflects the individual operational philosophy specific to each plant. This system standardizes operations by utilizing a rule-based framework that aligns with the plant's unique processes and goals. The VAiron BF Expert System ensures that operations are conducted in a consistent manner, minimizing deviations and enhancing overall plant efficiency.
Moreover, the system offers closed-loop control, which continuously monitors and adjusts the process parameters in real-time which increases the efficiency and productivity of blast furnace operations.

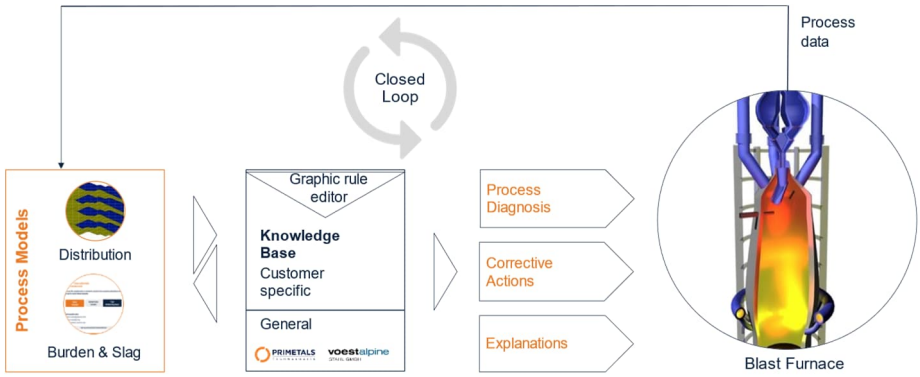

Figure 7: VAiron Expert System: Standardized, Rule-Based Operation

Finding optimal operating procedures for EAFs and consistently execute them with a Digital Steelmaking Assistant

In EAFs scrap qualities are usually mixed to create a blend that is then melted in the EAF. This blend can change on a daily, weekly, or monthly basis depending on the availability of raw materials, and it shall be adopted in view of the desired chemical composition and/or target use of the final steel product. Finding the best operating procedure for a given scrap composition is essential for optimized EAF operation and can be archived in a 5-step approach [5]:

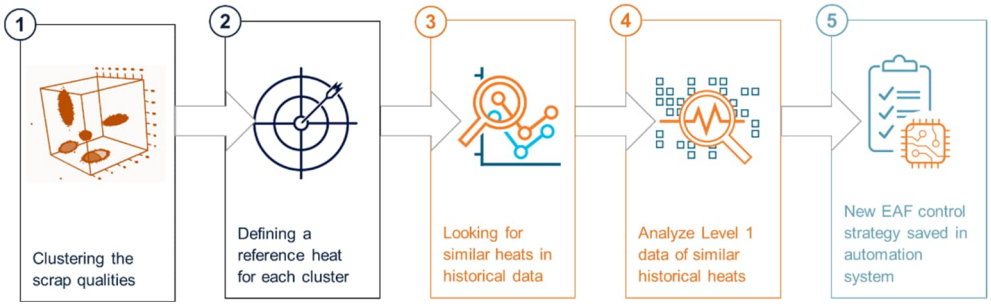

Figure 8: 5-step approach to find and execute optimized operating procedures on Electric Arc Furnaces

Once the scrap materials have been clustered by machine learning (ML), the historical data of the EAF is used to optimize the operations of the furnace cluster by cluster by finding the best practice for each cluster. In a second step a reference heat – the “golden batch” - for each scrap cluster is defined. The third step is to search for similar heats in historical data. Then a detailed analysis of the time-series data of the found similar heats is performed, based on pre-defined criteria and targets. Found similarities in the reference heats are likely to be the optimized operating procedure for the respective scrap cluster.

Having found the optimal operating procedure, in a last step this new know-how needs to be consistently applied in operation.

Primetals Technologies developed a Digital Steelmaking Assistant with the intention to incorporate available specific expert knowledge from various sources directly in the ongoing production process [6]. Sources can be expert know-how as well as know-how created by data analytics as described above. The Digital Assistant is integrated into the Process Optimization system and guides the operator through the entire production process.
Digital assistance for rule-based steelmaking enables less experienced furnace operators to achieve best practice results within a very short training period and it leads to a more unified production. The digitized know-how is conserved, consistently applied and forms the foundation for a continuous improvement process.

SUMMARY

This paper explores the transformative role of Artificial Intelligence (AI) in steel production, emphasizing how data quality and digitized domain expertise are critical for unlocking AI’s full potential. We outline the integration of machine learning and expert systems into key areas such as predictive maintenance, process control, and defect detection. We also highlight the unique challenges of steel production data - its complexity, heterogeneity, and real-time demands - and stress the importance of expert knowledge for applying reliable and explainable AI-driven decisions within production process. But we also point out the importance to know and understand the limits of AI-based techniques at the edge of their feasible regions.

A central concept is the “Effectiveness of Data” defined as the product of data quality, applied know-how, and implementation degree. The paper compares first-principle models with machine learning approaches, advocating for hybrid models that combine interpretability with predictive power. It also discusses strategies for maintaining data integrity, including balanced datasets, recalibration, and coping with changing operational conditions.

Three use cases illustrate practical benefits: Hybrid models for ironmaking quality prediction, expert systems for blast furnace optimization, and a digital assistant for electric arc furnace operations. These examples demonstrate how AI can reduce downtime, improve product quality, and support autonomous plant operation.

Looking ahead, steel production will face growing complexity in manufacturing advanced steel grades,

requiring tighter control and greater flexibility. There is a clear demand in the steel industry to push toward fully autonomous plant operations, supported by increasingly integrated systems and richer data availability. The principles and methodologies described in this paper mark the way how to approach this. As AI techniques continue to evolve, hybrid and explainable models will become even more sophisticated, enabling deeper insights and more reliable automation. The emergence of agentic AI - systems capable of autonomous goal-setting and adaptive learning - promises a new era of intelligent, self-directed plant control. These developments will be key to mastering future challenges and driving continuous innovation in the metals industry.

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PREDICTIVE-PRESCRIPTIVE QUALITY CONTROL IN THE STEEL INDUSTRY: A SYNERGY OF HUMAN KNOWLEDGE, MACHINE LEARNING AND AUTOMATION FRAMEWORK

Alessandro Stenico – PSI Software SE, Germany

In Quality Control for steel manufacturing, identifying a critical quality deviation at the finished product stage can be cost-intensive. Not only is the original order affected by delays due to late deallocation, but the reallocation of a finished product to a prime order becomes improbable, leading to financial loss. Predictive-Prescriptive Quality Control aims to minimize finished product downgrades through a two-step strategy: first, by anticipating downgrade risk at the earliest possible stage; and second, by offering the best solution to mitigate this risk during subsequent production steps or by suggesting early deallocation. To achieve this goal, predictive models of finished product characteristics are systematically integrated into quality control operations at every suitable production step. These models use upstream data collected throughout the material's history, as well as downstream production instructions and expected process results, requiring comprehensive knowledge of the entire production route. The prescriptive model "inverts" the prediction by suggesting downstream changes to the material-specific production instructions to meet the target at risk. A synergy of metallurgical knowledge and machine learning methods (relying on plant-specific historical data) looks promising for delivering useful models. To operate such Predictive-Prescriptive Quality Control in an industrial environment, a stable Quality Management framework is required to orchestrate each model and quality operation and ensure synchronization with the MES.

KEYWORDS: QUALITY – AUTOMATION – PREDICTION – PRESCRIPTION – MACHINE LEARNING

INTRODUCTION

In steel manufacturing, Quality Control is typically implemented as follows:

- Finished product inspection: Testing is conducted in accordance with the certification requirements defined by relevant international standards or customer specifications. Additional tests and inspections may be performed for internal quality assurance purposes – such as mitigating known customer-side issues – based on operational experience and quality history.
- Process monitoring throughout production: For each step of the production route, process parameters are monitored via Level 2 automation systems integrated into each production line. Deviations from target values or defined control ranges are flagged for evaluation and might be reviewed and approved prior to release the semi-finished product to the next production step.

In cases where nonconformities are detected in finished products, corrective actions may range from straightforward retesting to more extensive rework operations – or, in the most critical scenario, the deallocation of the material from the original production order. While successful retesting and rework typically incur limited additional effort in terms of resource consumption and delays in material dispatch, deallocation represents a significantly higher cost.

On one hand, replacing deallocated material to fulfill the original order may necessitate an entirely new production run, adversely impacting both the delivery timeline for the end customer and the scheduling of involved production lines within the facility. On the other hand, deallocated material will inevitably face some degree of downgrading, resulting in diminished commercial value. Furthermore, reallocating this material presents a substantial challenge: due to the advanced stage of processing and the high degree of product specialization, it is often exceedingly difficult to identify a compatible sales order with matching requirements such as chemical composition, technological properties, dimensional specifications, and surface finishing. As

a consequence, downgraded material may only be sold as a low-value commodity, often recovering little more than the cost of its raw inputs. In certain cases, it may ultimately need to be scrapped entirely.

Looking at the process control in each production step, Level 2 automation systems are responsible for ensuring compliance with defined process requirements across critical parameters such as temperature, speed, dimensional change, tension, etc. Target ranges for these parameters may be specified for quality assurance, i.e. to ensure alignment with product specifications, or for process optimization, i.e. to maintain stability and operational efficiency. Upon completion of each production step, the Level 2 system of the involved production line typically generates a comprehensive report documenting actual process conditions, with deviations from specified targets clearly identified. In these cases, decisions on nonconformity management are based on a trade-off between cost and benefit, based on available operational data, expert judgment, and previous experience.

However, manufacturing in the metals industry is a complex process. Numerous combinations of grades, dimensions, and surface finishes result in thousands of product variants, each potentially requiring distinct production routes that can critically influence the final outcome. The expertise related to these influencing factors is dispersed across specialized domains, making effective communication and timely feedback among stakeholders a persistent challenge in day-to-day operations. Additionally, personnel responsible for nonconformity management must navigate competing operational priorities that may conflict with quality assurance objectives. These pressures include meeting on-time delivery commitments, maximizing production yield, optimizing resource utilization, and minimizing inventory levels – all of which can complicate the consistent enforcement of quality standards.

Based on the considerations outlined above, the following quality control strategy is proposed:

1. Qualification of semi-finished products: Semi-finished products should be assessed, preferably at every production step, based on their potential impact on the quality conformance of the associated finished products. Evaluation must consider not only deviations in individual process parameters but also adverse combinations of parameters across different production steps.
2. Early response: Quality risks that jeopardize finished product compliance, identified as described above, should trigger corrective measures as early as possible within the production route.
3. Efficiency-driven reaction: Corrective responses should focus on the most efficient solution. Depending on the specific case, this may involve early deallocation or the implementation of compensatory actions. In general, the optimal compensatory measure is one that minimizes disruption to the planned material flow.

All three strategic elements should be supported by validated domain expertise and software automation in order to reduce error rates and minimize manual effort.

The next chapters present a solution framework addressing these requirements.

QUALITY PREDICTION

Challenge

The properties of finished steel products arise from the interactions among different “treatments” applied along multiple production steps executed on different production lines. While chemical composition is the foundation of each steel grade, further process parameters during steelmaking, casting, rolling, heat treatment, and finishing can exert an comparable significant influence.

The domain experts in the steel industry (including steel developers, quality engineers, production specialists, and application technologist) have developed a vast and highly specialized knowledge about the correlations between chemistry, process, steel microstructure and product properties. However, quantifying these interdependencies still remains challenging. This difficulty stems from the fact that industrial process conditions are profoundly affected by equipment-specific characteristics. For instance, a pyrometer measuring the surface temperature of a thin strip at the end of a long runout table in one hot strip mill does not, from a metallurgical

perspective, capture the same process attribute as a pyrometer assessing a thick, scale-covered strip on a short runout table in another mill.

Such variability in empirical data from industrial environments complicates efforts to generalize physical models that predict material properties based on process data as inputs. Consequently, any modeling approach – whether grounded in metallurgical principles, semi-empirical techniques, or numerical/statistical algorithms – requires extensive customization. This entails adapting models to available measurement inputs and calibrating them against historical production data, requiring a non-negligible effort.

Utilization in quality control

Assume that a validated predictive model is available, capable of estimating specific finished material characteristics with sufficient accuracy. Such a model typically requires a comprehensive set of input data collected throughout the entire production route. Once all relevant data has been gathered at the end of production, the target characteristic can be predicted. This offers some advantages:

- Physical testing for the predicted characteristic may be eliminated, resulting in cost and time savings (e.g. [1]).
- The predictive model can be applied across the entire "volume" of the material, enabling the identification of localized deviations affecting singled portions of material without physical sampling (e.g. [2]).

This approach enables a preliminary form of non-destructive testing across 100% of the production volume, using only data acquisition and computational analysis. More resource-intensive physical investigations can then be confined to materials identified as being at elevated risk for nonconformity.

An even more effective application of predictive modeling in quality control, outlined in the previous chapter, involves forecasting the finished product's properties at an intermediate stage of production. This allows for early identification of potential quality risks. The same validated predictive model developed for the finished product can be utilized for this purpose. However, when applying the model to a semi-finished product, two distinct categories of input data must be considered:

- For the upstream (completed) production steps: Actual process data are available.
- For the downstream (pending) production steps: Expected process data has to be provided to the model by the user. These estimations can be derived from process instructions, under the assumption that the upcoming steps will adhere to them. Alternatively, historical process data from comparable production runs can be leveraged to infer the missing inputs.

The predicted characteristic value for the finished product, calculated at this intermediate stage, can then be compared with the target specification. This enables a risk assessment regarding potential nonconformity, based on the current material condition and incorporating the cumulative influence of all prior and future process parameters. Such holistic evaluation far surpasses isolated parameter checks, offering a significantly more comprehensive and proactive approach to quality assurance.

QUALITY PRESCRIPTION

Definition

In this paper, the term quality prescription refers to the instructions derived for one or more process parameters, calculated to meet a defined quality requirement. These instructions specify the target values for downstream processes, taking into account the current condition of the material under analysis.

Since the predictive model estimates a characteristic y based on input variables $x_1, x_2 \ldots x_n$, which represent relevant process parameters and material attributes, it can be expressed as:

$$y = f(x_1, x_2 \ldots x_n) \quad (1)$$

Given a predictive model, the prescriptive model can be described as its “inverse function”. To prescribe a specific setting for x_1 that achieves a desired outcome value of $y = y_o$ (inpiut), assuming the other parameters $x_2 \ldots x_n$ (also input), the inverse operation is:

$$x_{1o} = f^{-1}(y_o, x_2 \ldots x_n) \quad (2)$$

It is important to note that f and f^{-1} need not be traditional mathematical functions. They may represent any type of computational model capable of producing the required outputs.

Utilization in quality control

Assuming a predictive model as described in equation (1) is available, it can be applied after any production step P to predict the value y_p of characteristic y for the finished product. This is achieved by feeding the model with:

- Upstream actual process data $(x_1, x_2 \ldots x_m)$ covering all process steps up to and including step P and
- Expected downstream process data $(x_{m+1}, x_{m+2} \ldots x_n)$ representing the anticipated parameters of subsequent process steps following P.

If the predicted value y_p indicates a high risk of failing to meet the required specifications for characteristic y of the finished product, a prescriptive reaction may involve modifying process instructions to influence selected parameters among $x_{m+1}, x_{m+2} \ldots x_n$. These adjustments aim to steer production toward an improved outcome, ideally achieving a value $y = y_{opt}$. The prescriptive model activated after production step P is responsible for generating new target values for specific downstream process parameters, e.g.:

$$(x_{m+1}, x_{m+2}) = f^{-1}{}_P (y_{opt}, (x_1, x_2 \ldots x_m)_P, (x_{m+3}, x_{m+4} \ldots x_n)_P) \quad (3)$$

This operation can be repeated after any production step ($P, P+1, P+2 \ldots$). The prescriptive model shall be modified accordingly, being aware of the restrictions affecting the modifiable process instructions downstream.

The extent to which downstream process parameters can be prescribed following a quality control operation, both in terms of type and quantity, is highly dependent on the available technology, the degree of process automation, and the inherent constraints of the production line. Any prescription must meet two criteria:

- Feasibility: Prescriptions must be realistically implementable.
- Compliance: Changes must not compromise other critical product requirements.

USE CASES

Mechanical properties

The mechanical properties of steel products (e.g. tensile strength, yield strength and elongation as result of a tensile test) are primarily determined by the material’s microstructure, which evolves throughout the different production steps, influenced by a range of factors. For instance, for hot rolled products, critical parameters include at least the chemical composition and the thermomechanical conditions during hot rolling (temperatures, thickness reductions, cooling rates etc.). For cold rolled and annealed steel strip, cold rolling, annealing and temper rolling specifics further influence the mechanical properties. And so on for other steel roducts.

Dedicated, steel grade specific models could be created to predict mechanical properties based on identified relevant data inputs collected along the entire production route.

The availability of such a validated predictive model enables the implementation of predictive-prescriptive quality control strategies for semi-finished products. As an illustrative case, this approach is described in the following to control quality after hot rolling, within the production route of cold rolled galvanized strip.

Necessary input data for prediction after hot rolling of the mechanical properties of the finished product could

be:

- For the upstream, executed production steps of steel making, casting and hot rolling: material dimensions, chemical composition, slab reheating temperature, hot rolling temperatures, rolling passes, runout table cooling pattern etc.
- For the downstream, not yet executed production steps of cold rolling, annealing and temper rolling: expected strip dimensions, set values for cold rolling passes, annealing settings (soak temperature, furnace atmosphere, controlled cooling), set values for temper rolling etc.

The predictive quality control operation would also consist in the following actions:

1. Collect for each hot rolled strip the above mentioned upstream as-is process data and downstream expected process data
2. Provide the data to the dedicated predictive model
3. Compute the mechanical properties (prediction)
4. Collect the model's prediction regarding the mechanical properties
5. Evaluate the risk of quality deviation based on the prediction and the (finished) product's requirements
6. Release or block the strip based on the defined company risk policy

If a specific hot rolled strip is identified as nonconforming and therefore blocked based on the predictive evaluation, a corresponding quality intervention is necessary. In this context, the prescriptive model provides a tool by recommending adjustments to downstream processing parameters, tailored to the evaluated material condition.

Acting as the inverse of the predictive model – see equation (3) –, the prescriptive model utilizes identical input data with the exception of the targeted process parameter(s) (x_{m+1} and x_{m+2} in equation (3)) to be adjusted as prescription output and with the addition of the input of the mechanical property target (y_{opt} in equation (3)).

For example, the model may be applied to determine an optimal soaking temperature for the continuous annealing line. Processing the flagged hot rolled strip under the new prescription heavily increases the probability of meeting mechanical property specifications, thereby supporting closed-loop quality control and minimizing the risk of producing out-of-spec products.

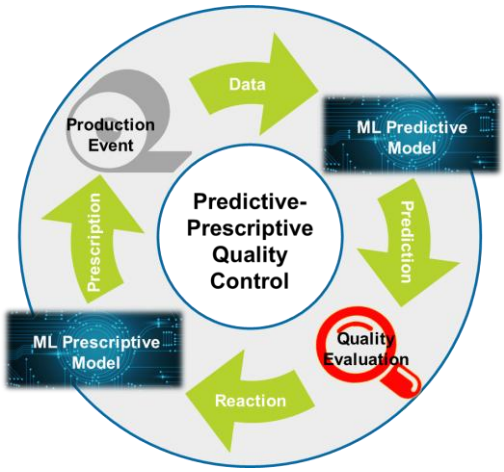

Fig. 1 – Closed-loop predictive-prescriptive quality control (schematic)

Reduction of the dispersion in technological characteristics

Beyond preventing outliers the test results for certification of finished products, the closed-loop predictive-prescriptive quality control approach (Fig. 1) can also be leveraged to minimize result dispersion within the

same steel grade or product. The corresponding strategy involves two key actions:

- Tightening internal evaluation thresholds by narrowing the target range for predictive quality evaluation
- Dynamically updating prescriptive parameters at each production stage

Implementing this strategy significantly influences the generation of process instructions for the Level 2 automation layer, enabling real-time updates aligned with each completed process step. While this dynamic approach may introduce additional efforts in scheduling, it offers a distinct advantage: the predictive-prescriptive loop actively steers operations toward optimal execution, using continuously refreshed process intelligence for each material unit.

FRAMEWORK FOR ML MODELLING

Machine Learning (ML) offers a highly promising methodology for the development of predictive and prescriptive models. However, in industrial domains such as steel manufacturing, the deployment of ML frameworks for modeling must satisfy a set of stringent requirements that are considered essential for practical implementation.

Explainability

To facilitate meaningful integration with human expertise, Explainable Artificial Intelligence (XAI), also referred to as White-Box AI, has gained prominence in recent years. The core objective of XAI is to provide ML models whose outputs are interpretable by domain specialists within the application field.

In industrial practice, White-Box ML models generate results that are visually accessible and explained through domain-relevant features. These features are defined by experts and typically offer more intuitive insight than abstract feature transformations derived from raw input data [3].

This approach enables domain experts to engage in constructive dialogue with data scientists, contributing their operational knowledge to the iterative refinement of model accuracy and robustness. Such human-in-the-loop collaboration is essential for developing credible and deployable models that earn the trust of practitioners whose workflows depend on their outputs.

Ultimately, only models that are transparent, validated, and trusted by domain experts will be successful and gain adoption within the steel industry.

Availability and stability

In a 24/7 industrial environment such as steel manufacturing, ensuring the availability and stability of all systems that directly influence operations is critical. Consequently, ML models used for predictive and prescriptive quality control must be deployed within an infrastructure that adheres to the same reliability standards as the Manufacturing Execution System (MES).

These operational ML models interface with the central Quality Management System through dedicated, standardized APIs. These APIs define precise data formats, payload structures, and communication endpoints, ensuring robust, seamless integration with related applications.

Importantly, the deployment environment is distinct from the ML development framework, where models are designed, trained, validated, and optimized. This separation maintains system integrity while enabling agile model iteration and performance improvement.

Monitoring

ML models deployed in manufacturing environments operate in dynamic conditions where data sources can undergo changes (in availability, stability or even content). Continuous, automated monitoring ensures that these models remain accurate, responsive, and aligned with real-world data, especially as process variables shift, sensor inputs drift, or equipment undergoes wear, recalibration or even substitution. Monitoring also helps

detect concept drift, identify model degradation, and trigger retraining workflows when necessary. Moreover, constant oversight of the results of the ML-based prescription enables compliance with the purpose of the prescriptive quality control and the swift resolution of anomalies. This “monitoring loop” follows the natural evolution of the industrial environment.

FRAMEWORK FOR PREDICTIVE-PRESCRIPTIVE QUALITY CONTROL

While the ML framework is tasked with the development, validation, monitoring, and lifecycle management of predictive and prescriptive models, the operational integration and governance of these models are handled by the Quality Management System (QMS) – see Fig. 2. The QMS is responsible for ensuring that the models are executed reliably and consistently as service-based tasks. To fulfill this role, the QMS must provide the following necessary infrastructure.

Collection of input data

The computation of predictions or prescriptions require input data based on the material production history and the production order. This data must be aggregated from multiple production lines and may comprise both recorded measurements and process instructions, as described above. To ensure reliable model performance, input data must consistently adhere to predefined format and completeness standards. Achieving this involves:

- Collecting process data from disparate IT sources and consolidating it into a unified database with a harmonized schema via dedicated interfaces.
- Performing spatial data transformation into the coordinate system specific to the target material, while accounting for its complex production genealogy – especially in steel manufacturing, where operations such as rolling, slitting, welding, or coiling can significantly alter geometry.
- Validating the input data and establishing default handling procedures when required data are incomplete or noncompliant with model constraints.

Runtime orchestration and transparency

It is the responsibility of the QMS to determine the precise production step at which the predictive-prescriptive quality control strategy should be executed. This assignment need not be generic; rather, it should be flexible and tailored based on the availability of ML models, allowing different product types to be evaluated at distinct production steps or lines. To maintain operational flexibility, the sensitivity of model predictions evaluation must be configurable. This empowers the Quality Engineer to calibrate the influence of predictive-prescriptive analytics on the production flow.

These configurations must be intuitively manageable through a dedicated user interface that facilitates rule definition, model selection, and control parameter adjustment. Once configured, the QMS automatically orchestrates prediction and prescription tasks, triggered by production events. Outcomes must be presented transparently, enabling rapid review and adjustment without requiring modification to the underlying Production Execution Management system.

Updating the production order

The delivery of process instructions to Level 2 automation systems of the single production lines is conventionally managed by the Manufacturing Execution System (MES) as part of its production order management. A prescription dynamically generated by a prescriptive ML model becomes actionable only when it is properly transferred to and integrated within the MES. This integration is critical and necessitates the ability to update production orders dynamically in response to quality control outcomes.

Given that prescriptions are specific to individual material units, the production order management framework must support granular order definition at the material unit level whenever execution logic requires it. This capability must coexist seamlessly with broader production order functions, such as planning, material balancing, and resource allocation, without introducing conflicts or disruptions. Ensuring this compatibility preserves system integrity while enabling intelligent, responsive control over production instructions derived from ML-driven quality strategies.

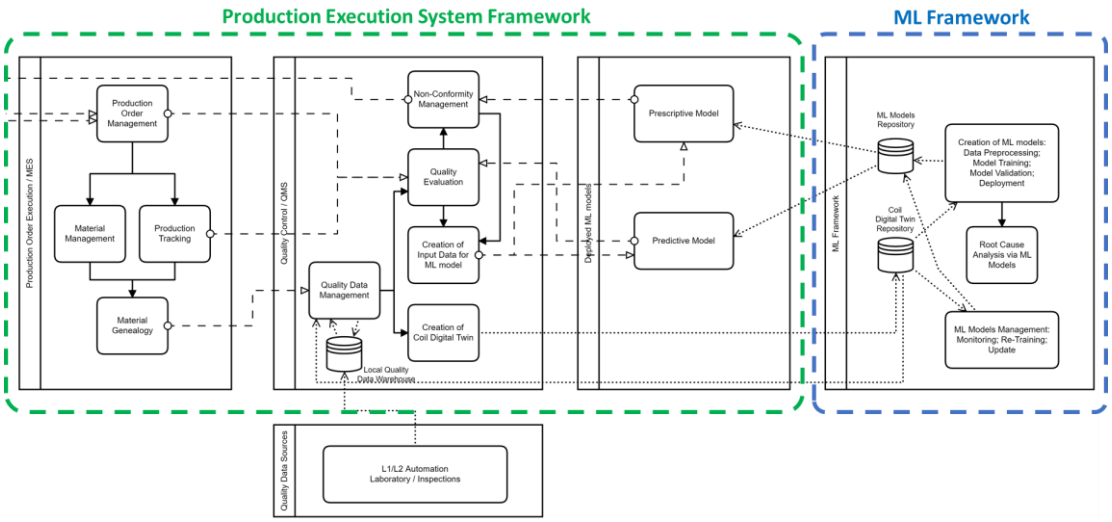

Fig. 2 – Example of solution architecture separating the MES/QMS framework from the ML framework: the ML models are managed within the ML framework but deployed within the MES/QMS framework.

CONCLUSIONS

Despite longstanding interest within the steel industry, large-scale implementation of predictive and prescriptive quality control mechanisms has been constrained by two key barriers:

- High model development effort: Developing robust, quantitative models requires extensive metallurgical domain expertise and advanced modeling skills.
- Integration complexity: Embedding these models within MES/QMS infrastructures entails nontrivial system interfacing, adaptation to heterogeneous systems, and alignment with operational constraints.

Recent progress in White-Box Machine Learning facilitates deeper integration of metallurgical domain knowledge with advanced analytics. This synergy enhances model robustness, fosters cross-disciplinary validation, and shortens the path to industrial implementations.

On the other side, mature Level 3 automation systems – spanning production order management, manufacturing execution, and integrated quality control – offer robust infrastructural capabilities to support deployment and execution of predictive and prescriptive models. When embedded within these systems, ML models can:

- React dynamically to incoming quality data via prediction and their evaluation
- Trigger fine-grained, material-specific process prescriptions
- Preserve consistency across planning and execution workflows

The convergence of explainable machine learning and advanced Level 3 automation systems can so unlock ML's potential for industrial quality control, leading to significant reductions in nonconformities, rework and downgrades.

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EXPLORING CAPABILITIES OF AN AUCTION-BASED MULTIAGENT SYSTEM IN REAL-TIME REACTIVE SCHEDULING

M. Gutierrez[1], J. Ordieres-Meré[1], E. Sirovnik[2], C. Nölle[3]
[1]Escuela Técnica Superior de Ingenieros Industriales, Universidad Politécnica de Madrid, Spain
[2]Thyssenkrupp Rasselstein GmbH, Andernach, Germany
[3]VDEh-Betriebsforschungsinstitut, Düsseldorf, Germany

In this paper, a distributed auction system intended to provide efficient real-time reactive scheduling for flat steel industry is introduced. We focus on the context of parallel finishing lines where several equipment units can be used to process the materials (coils). When a severe disruption takes place, it is necessary to provide a feasible reschedule in a timely manner [1-2].

Regarding the scheduling algorithm, both materials to be processed and processing equipment units are conceptualized as agents that participate in auctions. Likewise, a log agent registers all the information related to each auction. Regarding the algorithm logic, the main steps are the following:

- Once the successful creation of all the agents is confirmed, the log agent starts the auction logic by sending a message to the equipment units that are to be rescheduled.
- Each equipment sends a call for bids to all the materials available to be processed, alongside its current status and the price that led to the last assignment, which serve as a reference.
- With that information, each material calculates the amount to bid on and sends it to the equipment, which, in turn, calculates the costs associated with processing that material the next—adapting location, width and other adjustments that can be defined,—and subtracts it from the bid price to obtain the utility value.
- After receiving the bids from the materials, the equipment chooses the one that provides the highest utility value, sends a message to the corresponding material, which can then confirm its availability and, in case it was participating in other auctions, it also notifies the other plants that it has been already assigned.
- After each assignment, the equipment starts another round of bidding, until there are no materials available to be assigned.

The result of the algorithm is the sequence of materials to be processed at each equipment. Thus, through a series of bidding rounds the set of materials waiting to be processed are rescheduled from a multi-objective perspective. This approach enables implementing not only customer order-based material rules but also rules guiding the behavior of the material processing equipment units [3].

From the information technology viewpoint, the critical timing efficiency requirement is handled by setting a distributed environment and using Apache Kafka messaging [4]. The latter technology shows its efficiency in handling the information exchange required for the creation of auctions alongside the interaction of all the agents participating in each auction until the scheduling process is completed.

Finally, different configurations of the system are explored through a series of data scenarios. The analyses of the solutions yield the identification of needs for additional rules as well as further functionalities.

KEYWORDS: AGENT-BASED SCHEDULING – RESCHEDULING – FLAT STEEL PARALLEL LINES

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AI-POWERED CLASSIFICATION AND PREDICTION OF PROCESS DEFAULTS IN STEEL MANUFACTURING

Alfredo Formisano[(1)], Luca Gaia[(1)], Elena Geminiani[(1)]
Alessandro Ferraiuolo[(2)], Stefano Pantarotto[(2)], Umberto Liuzzo[(2)], Stefano Orselli[(2)], Davide Ricco[(2)]
[1] ICONSULTING SPA
Via Bazzanese 32/7, Casalecchio di Reno - Bologna, Italy
[2] Marcegaglia Steel SpA,
Via Baiona 141, Ravenna, Italy.
Email: alessandro.ferraiuolo@marcegaglia.com

To improve operational efficiency and minimize downtime, it is crucial to understand the causes leading to process defaults in the steelmaking industry. This study presents a generalized framework applicable across a wide range of metal-forming processes, which is based on an AI-powered solution designed to predict and classify breakages caused by process anomalies. The proposed solution identifies the operational phase in which failures occur as well as the key process variables (such as motor current and rolling force) that may act as breakage precursors. The objective is twofold: on one hand, to distinguish breakages attributable to process anomalies from those caused by material defects; on the other hand, to extract insights and meaningful interpretations of the mechanisms leading to plastic instability. A predictive model leveraging historical data from IoT devices is combined with statistical modelling to detect early warning signals associated with breakages. This integration of techniques allows proactive decision-making and adaptive process control. The study adopts a high-performing architecture that utilizes integrated services to process and analyze large-scale data streams in real time. This scalable infrastructure ensures efficient data handling and facilitates predictive analytics, ultimately enhancing process reliability. A practical application in the cold rolling scenario is presented, showcasing the potential of the proposed methodology in similar industrial settings.

KEYWORDS: AI MODEL - PLASTIC INSTABILITY - STRIP FAILURE - PROCESS OPTIMIZATION - ROOT CAUSE ANALYSIS

INTRODUCTION

This paper focuses on developing an AI-based approach to detect and correct process anomalies in real-time. In every stage of steel production, unexpected deviations and the occurrence of rolling force unbalances can lead to not compliant product quality, increased scrap, unplanned downtime, and significant economic losses. In continuous processing, such as hot and cold rolling mills, these risks are amplified by the high process speed and mass flow. In particular the cold rolling reversible mill process, where strip speed routinely changes from low speed in the start up phase up to a maximum speed of about 1000 m/min, presents quite huge challenges: high strain rates, complex interplay of strip geometry features, mechanical properties, thermal profile, and tribological factors could trigger defects occurrence and in some cases even the strip failure. Classical models, typically based on empirical equations, fail to interpret the fine mechanisms of the deformation process because they are characterized by numerous empirical parameters that require complex training activities. The idea underlying this research aims at leveraging the capability of AI models to ingest high-frequency sensor streams of the modern cold rolling plant in order to define AI agents capable of assisting operators in understanding events that arise from nonlinear conditions, complex interactions between variables and process anomalies both in terms of sharp variations on the strip length and in terms of transverse unbalance of process variables such as longitudinal tension, rolling force. Such approach could enable a shift from the conventional troubleshooting to proactive process optimization, reducing scrap rates and enhancing mill throughput. The first step of this research consisted in classifying the principal causes of strip failure related to uneven strip thickness profile, flatness problem, microstructural inhomogeneity, anomalous process conditions and recognizing them, in real-time, from the advanced analysis of process data. The present study introduces a novel approach centered on monitoring plastic instability through the online estimation of work

hardening within the roll gap. It is assumed that the rate of work hardening, defined as the derivative of flow stress with respect to strain, could play as a sensitive indicator of the onset of local necking in plane-strain conditions. By continuously evaluating this parameter, it becomes possible to detect conditions under which the strip shifts from stable to unstable plastic flow, often the precursor of strip failure, even before that the macroscopic defects arise. Establishing a robust taxonomy of failure modes, along with a consistent number of process variables characterising each failure mode, it was built up an AI-driven anomaly detectors and automated decision support systems. Real-time estimation algorithms must merge indirect observables (e.g., roll separating force, strip tension, strain, torque fluctuations) with physical based constitutive models. In this context, advanced AI techniques, ranging from recurrent neural networks for temporal pattern recognition to physics-guided machine learning that embeds incremental plasticity constraints, offer a pathway to robust deformation stability monitoring. In the medium terms it is expected that this approach of identifying and addressing process faults across steel manufacturing could become a real-time, predictive control. By classifying failure modes, extracting pertinent features from high-speed process data, and leveraging work-hardening-based instability metrics within an AI framework, the cold rolling process could improve the global productivity, quality and operational resilience.

The next sections highlight the proposed framework and the system architecture requirements. Then a practical application in the cold rolling scenario is illustrated, showcasing the potential of the approach. The last section gives directions for future research.

METHODOLOGY

The methodology proposed in this study is applicable to a wide range of systems within the steelmaking industry. Operational data, such as force, mill speed and tension, are typically acquired via dedicated data acquisition software. Sensors are strategically placed at key locations along the processing line, enabling real-time monitoring and logging of process variables throughout production. Given that strip failure is a sudden event, the analysis is conducted at a high temporal resolution, specifically at the millisecond level. However, the proposed framework is general and may handle data sampled at different rates. Let S be the total number of signals recorded for coil *i*, with *i = 1, … N*. We define the signal matrix $\mathbf{X}^{(\mathrm{i})} \in \mathbb{R}^{K_i \times S}$, where K_i is the number of discrete time steps sampled until the failure of the corresponding strip. The complete signal matrix $\mathbf{X}$ for N broken coils is constructed by vertically concatenating the individual coil matrices as follows:

$$\mathbf{X} = \begin{bmatrix} \mathbf{X}^{(1)} \\ \dots \\ \mathbf{X}^{(\mathrm{i})} \\ \dots \\ \mathbf{X}^{(N)} \end{bmatrix} \in \mathbb{R}^{K \times S} \qquad [1]$$

where $K = \sum_{i=1}^{N} K_i$ is the sum of the number of time steps for each coil. We identified five main causes of strip failure in a cold-rolling process, based on failure diagnostics and expert knowledge:

1. **Drive current anomaly**: a drop in drive current to zero leads to a line shutdown, resulting in strip failure.
2. **Insufficient emulsion**: inadequate emulsion flow or pression increases temperature and friction, ultimately causing strip breakage.
3. **Thickness spike**: exceeding the nominal strip thickness prompts a system halt and, in turn, failure.
4. **Non-compliant flatness**: misregulation in flatness control systems can lead to abrupt failure.
5. **Plastic instability**: when the material undergoes deformation beyond its stretch capacity, leading to strip failure, often related to inherent material defects.

Each failure mode is typically reflected in a subset of the available signals. For instance, drive current anomalies can be monitored via drive current measurements at the payoff and coiler positions, whereas a strip failure due to insufficient emulsion is traceable through the emulsion pression and flow signals. Non-compliant flatness, though harder to detect, is generally anticipated by variations in the signals controlling flatness, such as bending, tilting and shifting. Conversely, strip failure arising from plastic instability is generally not anticipated by any visible consistent signal patterns, and is more likely due to intrinsic material issues, such as inclusions or micro-cracks. When strip failure results from causes 1-4, the root cause can be attributed to anomalies in the cold-rolling process. In contrast, failure due to plastic instability suggests that the strip material itself may be defective.
In order to classify the coils based on strip failure cause, the following workflow is proposed.

1. Data Cleaning & Processing. Raw data must first be cleaned and processed to ensure suitability for analysis. Typical operations include resampling to the desired frequency, handling missing values, and discarding initial time segments prior to the onset of cold rolling.

2. Data Visualization. A series of plots and reports should be generated to visualize signal patterns and trends. We have found it to be particularly effective to focus on the last 5 seconds preceding strip breakage. Within this window, abnormal signal behaviour often emerges, which can help pinpoint the root cause of failure. Visualization also assists in identifying edge cases that may warrant special attention. For instance, if total force readings turn negative, this may indicate that the stand was open, a condition that, if overlooked, could lead to biased conclusions.

3. Operational phase identification. It is useful to identify the operational phase during which the failure occurred. The *working phase* during which the coil breaks can be determined by analysing the rolling mill speed. If the speed (or a variation thereof) is below a predefined threshold, the break occurred during a *transient phase*, typically characterized by oscillations and drifts. This contrasts with the *stable* phase, where operating conditions are steady. Transient phases can occur during either *acceleration* or *deceleration*. The deceleration phase, in particular, is identified via the activation of an automatic slowdown flag at failure time.

4. Strip failure cause identification. To identify the root cause of failure, we extract the last 5 seconds of signal data prior to breakage. To avoid incorporating post-failure effects, we discarded a brief buffer interval preceding the breakage flag issued by the PLC. This ensures the analysis reflects only pre-failure behaviour. The following workflow has been developed to classify the potential causes of strip failure.

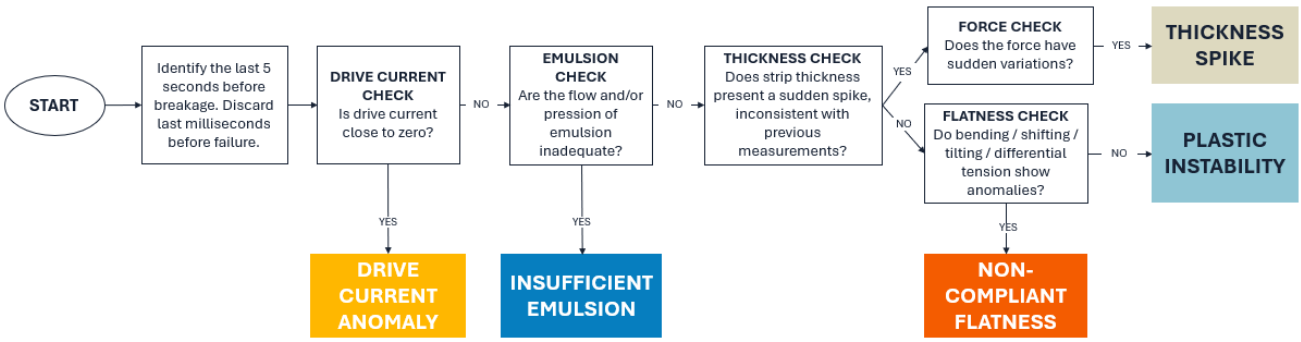

Fig.1 – Workflow for attributing the potential cause of strip failure based on signal diagnostics.

Some of the conditions illustrated in the diagram are rule-based, derived from expert knowledge of the production process. Others rely on statistical and mathematical indicators designed to capture trends, patterns and variations in the signals. Examples include computing the signal standard deviation over rolling windows, measuring the magnitude of the absolute difference between signal peaks and throughs, as well as estimating the slopes of the fitted trend lines. This method has been tailored for the above indicators, allowing it to detect anomalous variations in the monitored signals. The resulting framework serves as a foundation for more advanced analyses, including root-cause diagnostics and predictive modeling. By collecting data from historical strip failure events, it is possible to train machine learning models capable of learning from past data. These models can then predict the likely cause of future strip failures and identify the key process variables that may act as breakage precursors. Rapid and accurate identification of strip failure causes is critical for effective diagnostics. It enables early detection and malfunctioning equipment and supports proactive maintenance strategies aimed at minimizing downtime and ensuring process reliability.

SYSTEM ARCHITECTURE

The proposed system architecture (Figure 2) has been designed to guarantee robust ingestion, processing, and analysis of high-frequency time-series data generated by the cold rolling mill, while enabling real-time anomaly detection and predictive analytics at an industrial scale. The design adopts a cloud-native architecture on AWS, ensuring scalability, elasticity, and cost-efficiency for both streaming and batch workloads.
At its core, the architecture consists of four main layers:

1. **Data Ingestion Layer**. High-frequency sensor data from the rolling mill (e.g., forces, tensions, thickness, speed, lubrication parameters) is continuously collected by the IBA PDA system and securely transmitted to

the cloud through encrypted channels. To ensure interoperability across heterogeneous industrial environments, the communication leverages the OPC-UA protocol, a widely adopted standard for machine-to-cloud integration. Streaming ingestion is handled by Amazon Kinesis Data Streams, which guarantees sub-second latency, scalability, and fault tolerance, with buffering capabilities to manage peak loads. Data serialization uses compact, columnar formats such as Apache Parquet, improving storage efficiency and network performance.

2. **Processing and Feature Engineering Layer.** This layer combines AWS Glue for ETL orchestration with advanced stream processing capabilities provided by Amazon Kinesis Data Analytics for low-latency analytics. For large-scale transformations and feature engineering, Amazon EMR (with Apache Spark) executes distributed computations for time-series alignment, filtering, outlier detection, and engineered feature creation (e.g., rolling force variation, peak-to-peak indicators). Pipeline orchestration and dependency management are handled via AWS Step Functions, providing fault tolerance, monitoring, and automated retries. Data quality checks leverage AWS Glue Data Quality and Amazon Deequ to enforce integrity before datasets progress downstream. This architecture supports both real-time analytics and micro-batch processing, enabling predictive inference while maintaining a repository of historical datasets for retraining.

3. **Data Lakehouse and Model Management Layer.** Processed datasets are persisted in Amazon S3, forming the foundation of a data lakehouse architecture. Schema management and metadata governance are provided by AWS Glue Data Catalog, ensuring full lineage and compliance. The architecture includes Amazon SageMaker Feature Store for centralized feature storage and reuse, facilitating model consistency between training and inference. Machine learning development and lifecycle operations are orchestrated entirely with Amazon SageMaker, leveraging built-in algorithms, managed training environments, Jupyter-based notebooks, and SageMaker Pipelines for automated CI/CD workflows, testing, and drift monitoring. The approach adheres to MLOps best practices, ensuring reproducibility and operational resilience.

4. **Inference and Visualization Layer**. Predictive models are containerized and deployed using Amazon Elastic Kubernetes Service (EKS) for scalable and resilient orchestration. Inference endpoints are exposed via Amazon API Gateway, ensuring secure, low-latency communication with downstream systems. This architecture supports both real-time streaming inference and batch predictions for retrospective analysis. Visualization and decision support dashboards are delivered through Amazon QuickSight, enabling anomaly detection insights, predictive alerts, and process KPIs in an interactive interface accessible across devices.

The entire platform enforces enterprise-grade security through AWS Identity and Access Management (IAM) for role-based access control, AWS Key Management Service (KMS) for encryption at rest, and TLS for data in transit. Operational resilience is guaranteed by integrated observability, leveraging Amazon CloudWatch for real-time logging, alerting, and performance monitoring. This architecture is future-ready, supporting extensions such as AWS IoT Greengrass for edge computing and reinforcement learning frameworks for adaptive process optimization.

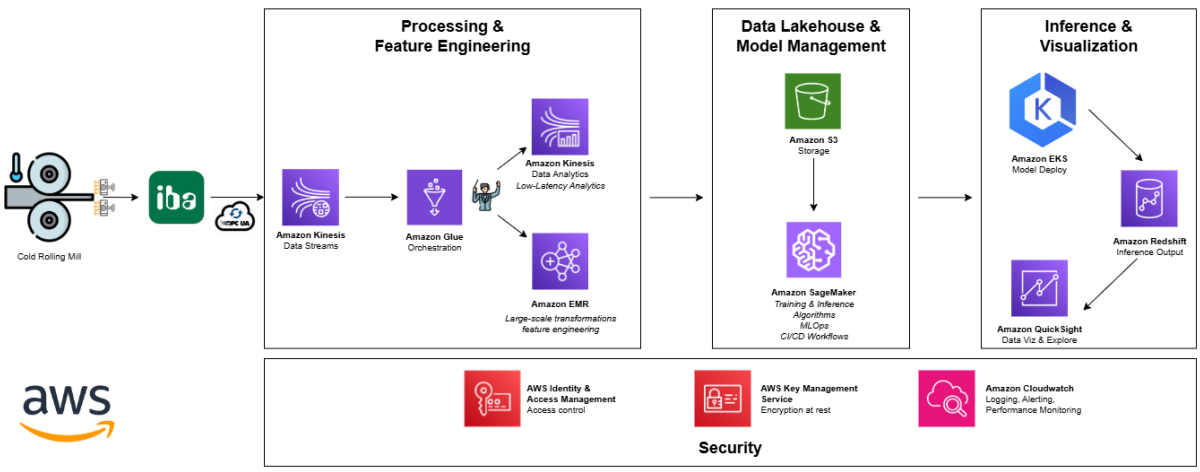

Fig. 2 – The proposed cloud-native system architecture on AWS.

RESULTS

We present a practical application of the proposed methodology at the cold-rolling mill of the Marcegaglia plant in Ravenna, Italy. The analyses included about 20 documented cases of strip failures. The set of available signals, continuously measured during the cold-rolling phase for each coil, is summarized in Table 1, along with a brief description of each variable. Raw signals were acquired using ibaPDA (Process Data Acquisition) software and sampled at every millisecond. For the purposes of the subsequent analysis, the data were resampled at 5-millisecond intervals to reduce computational load while preserving signal fidelity.

Tab. 1 – Summary of the operational signals monitored during the cold-rolling phase.

Signal	Unit	Description
Drive Current	A	Refers to the control of the electric motor that drives the rolling rolls based on the absorbed current.
Motor Current	A	Current drawn by the electric motor powering the rolls.
Emulsion Flow	lt/min	Flow rate of the emulsion fluid used to cool and lubricate the material and rolls during rolling. It increases as mill speed increases.
Emulsion Pressure	bar	Pressure at which the emulsion is sprayed onto the material. It increases as mill speed increases.
Thickness	mm	Strip thickness measured at different positions along the rolling line.
Thickness Reduction	%	Percentage reduction in thickness compared to the initial coil thickness.
Total / Motor side / Operator side Tension	kN	Mechanical tension applied to the steel strip: - Total: across the entire width of the strip; - Motor side: on the drive side of the stand; - Operator side: on the opposite side where the operator is positioned.
Differential Tension	%	Percentage difference in tension between the operator side and the motor side.
Total / Motor Side/Operator Side Force	kN	Force exerted by the rolls on the strip during rolling: - Total: total applied force; - Motor Side / Operator Side: contribution from each side. It increases with the increase of thickness reduction.
Differential Force	kN	Force difference between the operator side and the motor side.
Mill Speed	m/min	Speed at which the steel workpiece travels through the rolling mill line.
Mill Speed Setpoint	m/s	The desired speed value that the control system must maintain during the rolling process to achieve the required specifications.
Auto Slow Down Mode	Binary flag	Binary flag indicating whether automatic slow-down mode is active. The auto slow-down mode automatically reduces mill speed towards the end of the pass.
Bending	kN	It is used to control the strip's flatness whenever the CVC (Continuously Variable Crown) has an excessive absolute value.
Lower/Upper Shifting	mm	Horizontal displacement of lower and upper rolls. Automatic response to alter strip flatness.
Tilting	mm	It detects any lateral misalignment of the roll gap on the material.
Work Roll Km	Km	Total distance covered by the surface of the work rolls.
Lower/Upper Work Roll Diameter	mm	It refers to the diameter of the lower and upper work rolls that come into direct contact with the material being rolled.
Rolling Pass Number	Integer	It indicates the sequential number of the rolling pass for the current coil.
Strip Failure	Binary flag	The moment when the strip breaks during the rolling process as signalled by the PLC.

A graphical depiction of the two-stand cold rolling mill is illustrated in Figure 3.

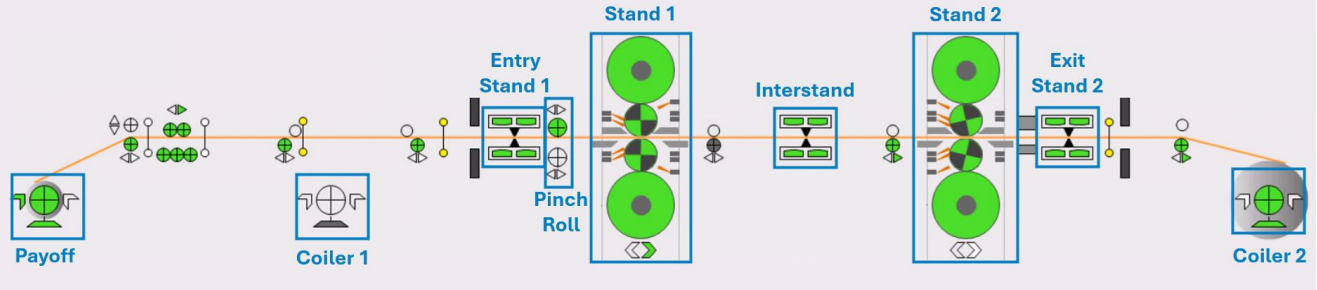

Fig. 3 – Schematic layout of the analyzed two-stand cold rolling mill.

Depending on their type, the signals were recorded at different locations within the plant, as summarized in Table 2.

Tab. 2 – Mapping of the analyzed signals to their respective sensor locations along the cold rolling mill.

	Payoff	Coiler 1	Entry stand 1	Pinch roll	Stand 1	Interstand	Stand 2	Exit stand 2	Coiler 2
Drive current	X	X		X	X		X		X
Motor current					X		X		
Emulsion Flow					X		X		
Emulsion Pressure					X		X		
Thickness			X			X		X	
Thickness Reduction					X		X		
Total Tension			X					X	
Tension (Motor side, Operator side, Differential)			X			X		X	
Total Force					X		X		
Force (Motor side, Operator side)				X	X		X		
Differential Force					X		X		
Mill speed setpoint			X						
Mill speed			X			X		X	
Bending					X		X		
Shifting (Lower and Upper)					X		X		
Tilting					X		X		
Work Roll Km					X		X		
Work Roll Diameter (Lower and Upper)					X		X		

As part of the data cleaning procedure, we excluded from the analysis the initial phase prior to the onset of cold rolling. The cold rolling process is considered to begin once both stands register positive force, and both thickness and mill speed are above zero. The processed signals were then visualized using interactive diagnostic plots, enabling users to explore signal trends and zoom with adjustable granularity. Figure 4 presents an example of the implemented *Coil Diagnostic Viewer Report*.

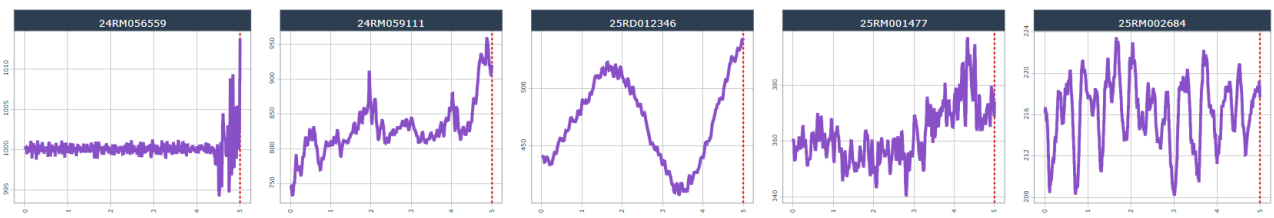

Fig. 4 – Example visualizations from the *Coil Diagnostic Viewer Report*. Each panel displays a line plot of a single signal (specifically, bending at stand 2) for different coils. The red dotted vertical line marks the recorded time of strip breakage. Only the final five seconds of signal data prior to failure are shown, enabling inspection of pre-failure behaviour.

In the following, we present the results of the workflow described above for two representative coils.

Coil 24RM056128

The failure for this coil occurred during the second pass, which begins at stand 2, and proceeds through to stand 1. By applying the previously described workflow, the failure was attributed to a *thickness spike.* This is evident from a sharp dip in the interstand thickness signal, shortly before the breakage event (Figure 5), where the thickness suddenly drops to a value near zero. The thickness anomaly causes fluctuations in the total force, ultimately causing strip failure.

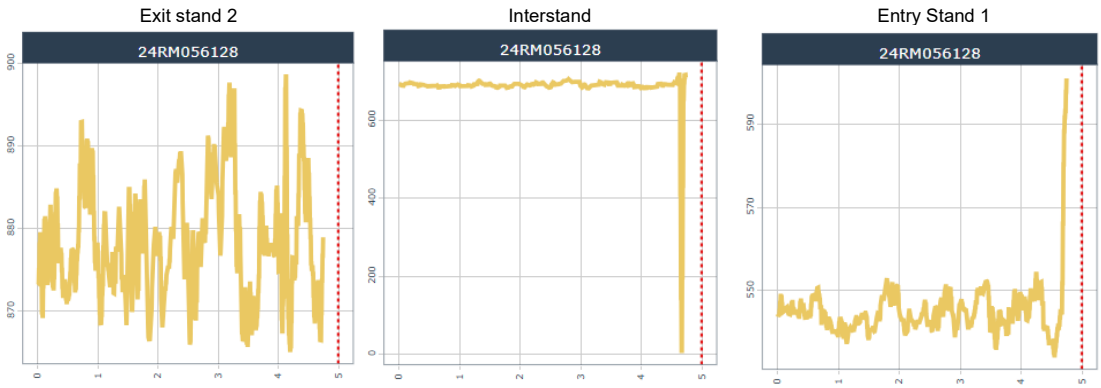

Fig. 5 – Graphical representation of thickness signal for coil 24RM056128 during the five seconds preceding failure (a buffer interval of 250ms prior to recorded breakage was discarded). The coil was in the second pass, entering from the exit of stand 2, progressing through the interstand, and finally reaching entry stand 1.

To identify the operational phase during which the failure occurred, we examined the rolling mill speed. Figure 6 displays the speed measured at the exit of stand 2, both in the five seconds leading up to the failure (left panel) and across the entire time series (right panel). The strip break occurred approximately 8 minutes after the start of the cold-rolling phase. As shown in both plots, the coil was operating in the stable phase, having completed all acceleration ramps and running at a steady speed of about 400 m/min.

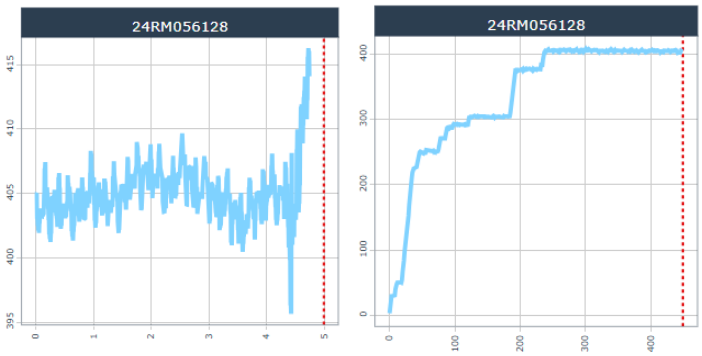

Fig. 6 – Graphical representation of the rolling mill speed signal for coil 24RM056128 at the exit of stand 2 during the five seconds before failure (left panel) and over the entire temporal range (right panel).

Coil 25RM008403

The failure for this coil also occurred during the second pass. Upon inspection of the drive currents, emulsion flows and thickness, no clear anomalies or distinct patterns were observed. Following the established workflow, we proceeded to investigate flatness-related indicators, specifically bending, shifting and tilting in both stands (Figure 7). As shown in the plots, shifting and tilting signals did not exhibit any noticeable deviations. However, the bending at stand 1 revealed a pronounced and increasing trend, from approximately 500kN to over 800 kN, in the moments leading up to the failure. This pattern indicates that the operator was actively attempting to correct a flatness issue in real time. This operation lastly resulted in strip failure. For this reason, the strip is attributed to be broken due to non-compliant flatness.

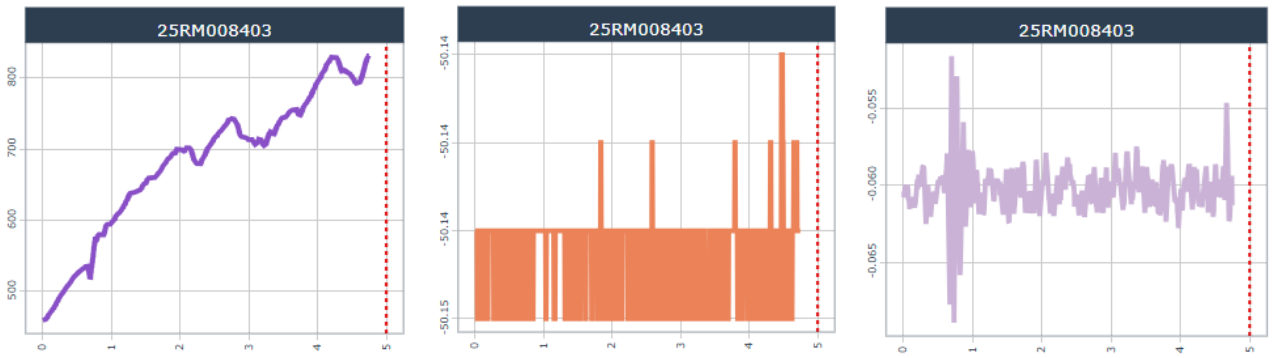

Fig. 7 – Graphical representation of bending (stand 1), lower shifting (stand 1), and tilting (stand 1) signals, respectively, for coil 25RM008403 during the five seconds preceding failure.

To determine the operational phase, we examined the rolling mill speed both five seconds prior to breakage and over the full time range (Figure 8). The data indicate that the coil broke during the transient acceleration phase, as the mill was still attempting to ramp up speed.

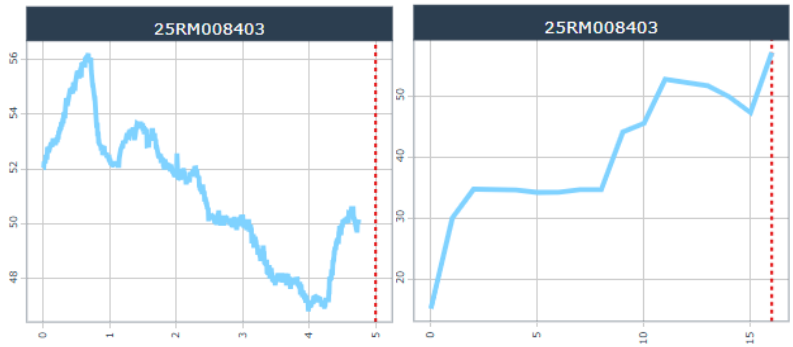

Fig. 8 – Graphical representation of the rolling mill speed signal for coil 25RM008403 at the exit of stand 2 during the five seconds before failure (left panel) and over the entire temporal range (right panel).

CONCLUSIONS

This paper presents ongoing research aimed at automatically classifying strip failures based on diagnostic data derived from real-time operational signals within a steelmaking process. The proposed strip failure mode attribution workflow identifies five main failure causes, each associated with distinct variations, patterns, and trends in key process indicators. A practical application in a cold rolling mill context demonstrated the potential of the methodology to enhance diagnostic capabilities and provide actionable insights. Preliminary results confirm that signal-based indicators can meaningfully characterize failure types and guide failure attribution. Future work includes scaling the workflow to a broader set of failure events and developing a predictive machine learning model trained on historical data. This model would enable early detection of warning signals, provide the probability of each failure cause, and support real-time diagnostics. Incorporating advanced anomaly detection techniques and time series modelling can help uncover hidden patterns in the data, contributing to a deeper understanding of the failure mechanisms. Ultimately, these tools can empower operators with proactive and AI-assisted decision-making and enable adaptive control strategies, thus enhancing reliability, reducing downtime, and improving overall process efficiency.

Performance of AI Oriented Contrastive Learning vs Convolutional Neural Networks (CNNs) in Quality Assessment of Zinc Coating Steel Coils

Amir Farmanesh, Alejandro Álvarez Castro, Joaquín Ordieres-Meré, Ahmad Rajabi, Jens Brandenburger, Daniel Falkowski, Miguel Gutiérrez

***Abstract*—Zinc-coated steel coil quality inspection is critical within the automotive and construction industries, where coating defect affects durability and safety. This study compares Contrastive Learning with Convolutional Neural Networks for the identification of defects in 4,482 coil profiles against zinc thickness measurements. CNNs, including normalization and pooling layers, delivered high accuracy (F1-score: 0.93 test, 0.75 gold-standard), and contrastive learning, utilizing Siamese networks, demonstrated less but improvable performance (F1-score: 0.61 raw, 0.66 preprocessed). CNNs perform well when there is abundant labeled data, while contrastive learning improves feature representation with scarce supervision. The results indicate the potential of AI for real-time quality control and the importance of data preprocessing to maximize model performance.**

Zinc Coating, Industrial Inspection, Quality Control, Contrastive Learning, Convolutional Neural Networks

I. Introduction

Zinc-coated steel coils play a pivotal role in multiple industries, such as automotive, construction, and appliance manufacturing by providing superior corrosion resistance and overall durability [1], [2].

Galvanized steel coils are manufactured by applying a protective zinc coating to steel, significantly enhancing their corrosion resistance and extending their service life [3].As shown in Figure 1, the hot-dip galvanizing process involves immersing steel in a bath of molten zinc. This method, in particular, offers numerous advantages, including outstanding durability, exceptional strength, and superior weather resistance [4]. These attributes make galvanized steel coils a preferred material across various industries, underscoring the critical importance of quality control.

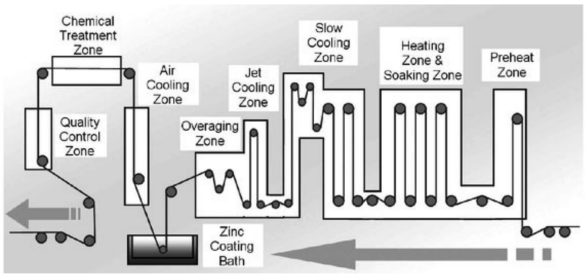

Fig. 1. Hot-Dip-Galvanizing-Line [5]

In the automotive sector, for instance, galvanized steel is critical for ensuring vehicle safety and durability, making rigorous quality control processes essential. Traditionally, as shown in Figure 2, these processes rely on visual inspections by human operators or rule-based systems ,supplemented by technologies like X-ray gauges and high-definition cameras that use measurements such as thickness gauges [6]. However, such methods are labor-intensive, prone to human error, and often struggle to handle the high variability and volume of modern production lines.

Fig. 2. Inspection System [5]

In recent years, artificial intelligence (AI) solutions have gained traction as an effective means to automate and enhance the accuracy of quality inspection [7]. Among various AI approaches, Convolutional Neural Networks (CNNs) have become a cornerstone of image-based classification and defect detection tasks because of their ability to learn hierarchical feature representations from large datasets [7]. Despite their success, CNNs typically demand extensive labeled data—a resource that is both expensive and time consuming to obtain in industrial contexts. To address the challenges associated with limited labeled data, contrastive learning (CL) has emerged as a self-supervised learning technique capable of leveraging unlabeled samples [8]. By comparing pairs of "similar" (positive) and "dissimilar" (negative) examples, contrastive learning discovers meaningful feature embeddings without relying solely on large amounts of annotated data [9]. This characteristic makes CL an attractive alternative in industrial settings, where annotation costs can be prohibitive and defect classes are highly imbalanced [10]. Against this backdrop, this paper systematically compares CNN-based and contrastive learning approaches for quality assessment of zinc-coated steel coils. We examine performance metrics such as accuracy, precision, recall, and F1-score, and also evaluate the robustness of each model to noise and data variability. Beyond the technical evaluation, we discuss the practical implications of deploying these methods in real-world manufacturing lines, aligning our findings with the emergent trends of Industry 4.0 and Industry 5.0, where intelligent automation is paramount.

II. State of Art

Convolutional Neural Networks (CNNs) have revolutionized the field of computer vision and have found extensive applications in industrial inspection [7]. Their ability to automatically extract hierarchical features from images by applying various layers (Figure 3) makes them particularly suited for tasks such as defect detection and classification [11] .

In the context of manufacturing quality control, CNNs have been employed to identify surface defects, measure coating thickness, and categorize different types of imperfections [12] . Recent advancements have focused on optimizing CNN architectures for real-time processing on embedded hardware, enhancing their applicability in industrial settings [11].

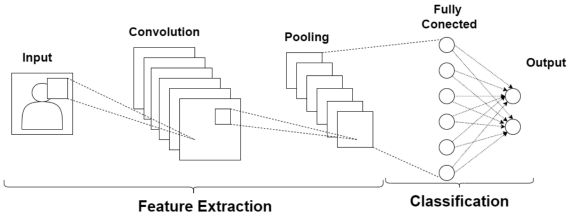

Fig. 3. CNN Layers

Contrastive learning, a self-supervised learning paradigm, has emerged as a powerful technique for learning representations from data without the need for extensive labeled datasets [8]. This approach involves training models to distinguish between similar and dissimilar data pairs, thereby learning invariant and discriminative features [10] .

Contrastive learning has been successfully applied in various domains, including natural image classification, medical imaging, and industrial inspection [13]. In industrial settings where labeled data is often difficult to get, contrastive learning offers a promising solution by leveraging both labeled and unlabeled data to train robust models [14]. In the specific domain of zinc coating steel quality assessment, traditional methods rely on image processing techniques and conventional machine learning algorithms to detect defects such as micro-cracks and uneven coating [12]. However, these methods often struggle with the variability in image conditions and the complexity of defect patterns, leading to suboptimal performance [15].

The integration of deep learning techniques, including CNNs and contrastive learning, represents a significant advancement in handling this variability while maintaining high accuracy [16]. Additionally, contrastive learning frameworks, such as Siamese net-

works, have shown promise in one-shot learning for defect classification [17].

Despite these advances, the application of contrastive learning in industrial inspection is still nascent and faces challenges related to data scarcity and computational demands [18]. This study aims to contribute to this evolving field by providing a comprehensive comparison of CNNs and contrastive learning approaches for quality assessment of zinc coating steel coils. By evaluating their performance under varying conditions and data availability, this research seeks to offer insights into the most effective strategies for implementing AI-driven quality control in manufacturing processes.

III. Methodology

A. Design Science Research (DSR) Approach

This research adheres to the principles of Design Science Research (DSR), drawing on structured methodologies highlighted by [19], [20]. By following DSR, the study pursues a systematic cycle of problem identification, artifact creation, evaluation, and result dissemination within the specific context of zinc coating quality assessment.

First, we clearly identified a persistent problem in industrial manufacturing, which is the difficulty of achieving accurate and efficient detection of defects in zinc-coated steel coils, especially when labeled data are limited. Next, we defined our research objectives, focusing on developing machine learning models—both Convolutional Neural Networks (CNNs) and Contrastive Learning (CL) frameworks—to enhance feature extraction and classification robustness.

Under the design and development phase, we formulated a dual-strategy approach,which include a CNN that relies on extensive labeled data, and a CL method capable of leveraging unlabeled data through self-supervised or semi-supervised learning. In order to demonstrate and evaluate these artifacts, we tested both models on a dataset of zinc coating images, comparing metrics such as accuracy, precision, recall, and F1-score. We also assessed each model's practical feasibility by examining computational overhead and sensitivity to data transformations.

Finally, as per DSR guidelines, we communicate our outcomes in both academic and industrial forums, discussing model performance, limitations, and possible avenues for integration into existing manufacturing processes. This iterative DSR cycle ensures that our solutions align with real-world requirements, thus bridging the gap between theoretical development and applied engineering practice.

B. CRISP-DM Framework

In parallel with DSR, we employed the Cross-Industry Standard Process for Data Mining (CRISP-DM) [21] to structure our data-centric tasks and maintain rigor in model development and evaluation. As can be seen

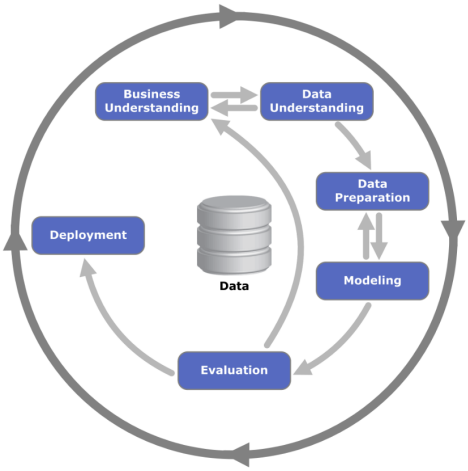

Fig. 4. Methodology CRISP-DM

in Figure 4 ,this methodology include several steps as follows:

- **Business Understanding:** We aligned the research with the operational needs of zinc coating inspection, recognizing that reduced downtime and improved defect detection accuracy translate into substantial cost savings and enhanced product quality.
- **Data Understanding:** Initial assessments of the zinc coating image dataset revealed various defect types,those ranging from cracks to inconsistent thickness, and underscored the importance of handling class imbalance.

- **Data Preparation:** We implemented normalization, augmentation such as rotations, flips, scaling, and row/column permutations, and optional segmentation masks for defective samples. These steps aimed to minimize the effects of lighting and positional variance while also addressing class imbalance.
- **Modeling:**We then developed CNN and CL models, conducting grid searches to tune hyperparameters such as learning rate and batch size. Model depth ranged from three to ten convolutional layers, and the placement of pooling, normalization, and dense layers was systematically varied to identify optimal designs.
- **Evaluation**Performance was measured through cross-validation and a final assessment on a gold standard set of images. Metrics such as F1-score, precision, recall, and ROC/AUC were used to capture both classification accuracy and model robustness.
- **Deployment:**Although the focus of this study is empirical evaluation, the eventual aim is to integrate the best-performing solution into an industrial inspection pipeline, emphasizing scalability and ease of maintenance.

IV. Proposed Solution

A. Data Collection and Preprocessing

The data utilized in this study was provided by an industrial partner, who shared a pre-collected, processed, and manually labeled set of coil measurements. Each coil was assessed based on zinc coating thickness, categorized either as acceptable (OK) or non-acceptable (NOK) by experienced operators (Figure 5). Nine sensors on each side of the coil captured these thickness measurements, resulting in 264 readings per sensor, which we established as a fixed parameter to enable efficient tensor operations.

To achieve this uniform dimension, each coil's length was segmented into 264 parts; coils that were shorter thus yielded a higher sampling density. Consequently, each coil produced a matrix of size 264×18 (nine sensors on each side), and combining multiple

Fig. 5. Zinc Measures

coils led to a dataset shaped as (N, 264, 18), where N is the total number of coils .

An inherent challenge in this dataset was class imbalance, as the manufacturing process typically yields a higher proportion of OK coils. To address this, we applied data augmentation techniques [22], including random row and column permutations, among other transformations. This step was crucial for increasing the number of NOK samples and helping the models generalize more effectively to unseen cases [23].

After augmentation, the main dataset comprised 4,482 images, which were partitioned into training, validation, and test subsets for model development and hyperparameter tuning. In addition to these subsets, a curated "gold standard" set of 60 images (30 OK and 30 NOK) was set aside, following the methodology suggested in [24]. This gold standard subset allows different models to be compared on an identical, unbiased reference, thereby offering a more definitive assessment of their predictive performance.

B. CNN Implementation

For the CNN-based solution, we designed an adaptable framework capable of generating different network configurations from a YAML specification file. Each configuration defines key parameters such as the number of convolutional layers (ranging from 3 to 10), the placement of pooling and normalization layers, dropout probabilities, and the depth of fully connected layers. Convolutional layers typically use ReLU activations, with kernel

sizes and numbers of filters adjusted to capture both coarse and fine-grained features of the zinc coating.

Once a configuration is parsed, a CNN model is constructed using the TensorFlow deep learning library. During training, we employ a categorical cross-entropy loss and an optimizer , refining hyperparameters through grid search or validation feedback. To ensure statistical robustness, each configuration undergoes 5-fold cross-validation, repeated up to 10 times, thus generating multiple performance measures,including accuracy, precision, recall, F1-score, and ROC/AUC. We further validate top performing models on a dedicated "gold-standard" set of 60 images, providing an additional checkpoint for borderline defect cases. This systematic approach to CNN architecture design and evaluation establishes a reliable baseline for automated zinc-coated coil classification.

C. Contrastive Learning Implementation

To overcome the limitations of limited labeled data and to exploit unlabeled samples, we integrated contrastive learning into our proposed solution in two principal ways. The first approach was SimCLR-inspired, where each image was augmented twice to form a positive pair, and images drawn from different samples served as negatives. A CNN backbone extracted features, which were then projected into a latent space via a small MLP head. Training relied on the NT-Xent loss, pushing positive pairs closer in the embedding space while separating negative pairs.

The second approach employed a Siamese network, in which two identical CNN encoders processed image pairs to produce embeddings. Positive pairs included two images from the same class ("OK" or "NOK"), while negative pairs mixed classes. To facilitate classification, reference images for each class were identified using clustering algorithms such as DBSCAN or KMeans, enabling new samples to be classified based on similarity metrics.

Once each cluster was formed, representative images that best characterized the center

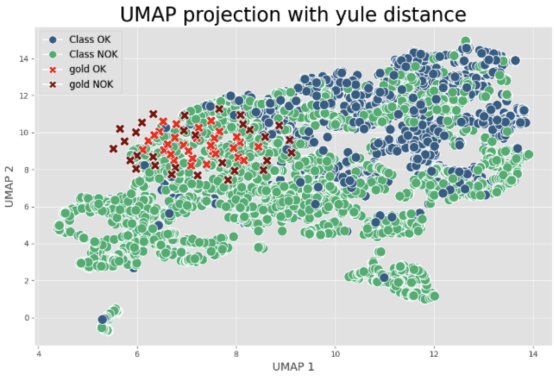

Fig. 6. Example of how embeddings from the same class form a single cluster

of these clusters were chosen to serve as references for class assignment.

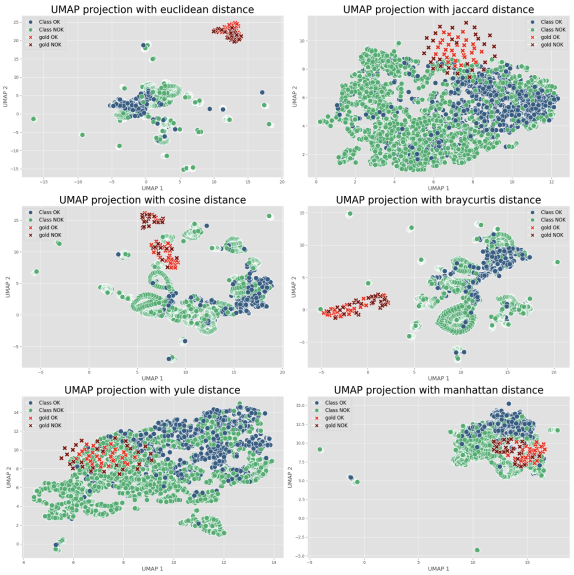

Fig. 7. Visualization of multiple clusters for OK and NOK classes using DBSCAN

After either type of contrastive pretraining which are SimCLR or Siamese,the encoder underwent a fine tuning phase with cross-entropy loss on the labeled dataset to finalize class predictions. This two stage process allowed us to leverage both labeled and unlabeled data more effectively, particularly in situations where annotated samples were limited.

D. Training and Evaluation

The implementation used TensorFlow and keras Python-based deep learning libraries and took advantage of multi-GPU training

for efficient experimentation. We systematically measured accuracy, precision, recall, F1-score, ROC/AUC, and inference time on both the test set and a highly curated gold standard subset of 60 images. The CNN models generally exhibited strong baseline performance with abundant labeled data, while the contrastive learning methods showed enhanced robustness, especially in identifying subtle defects and handling data scarcity.

V. Result

A. CNN Model Performance

The study began by testing a wide array of CNN configurations which initially several thousand,to explore the effects of varying convolutional layers (3 to 10), dense layers (3 to 11), and hyperparameters such as kernel sizes and dropout rates. Although deeper networks often performed better, most architectures still attained high accuracy and F1-scores, indicating that CNNs are well-suited to discerning acceptable (OK) from non-acceptable (NOK) coils. For instance, Figure 8 illustrates how adding more convolutional layers tends to improve classification, particularly when detecting borderline defects.

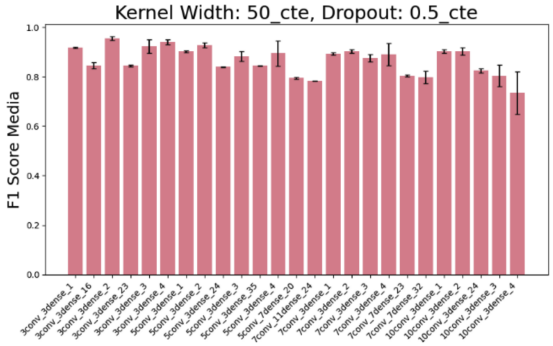

Fig. 8. Architecture Comparison

Despite these improvements, hyperparameter changes like adjusting kernel sizes or increasing dropout, generally yielded only minor differences, a conclusion supported by Shapiro–Wilk and t-tests statistical tests. In other words, CNNs of moderate to high depth could achieve similarly robust results, suggesting that overall design simplicity may be more important than fine-grained hyperparameter tweaks. The top architectures attained F1-scores above 0.90 on the main test set, yet on the smaller "gold standard" set of 60 curated images, their performance saw a modest dip, dropping to around 0.75–0.80. This gap underscores the difficulty of capturing subtle edge cases. As shown in Figure 9, confusion matrices confirm that most errors arise from classifying marginal NOK samples as OK (or vice versa), highlighting the nuanced nature of real-world zinc-coating defects. Overall, the CNN approach delivers strong, consistent results and provides a solid foundation for automated quality assessment in steel-coil manufacturing processes.

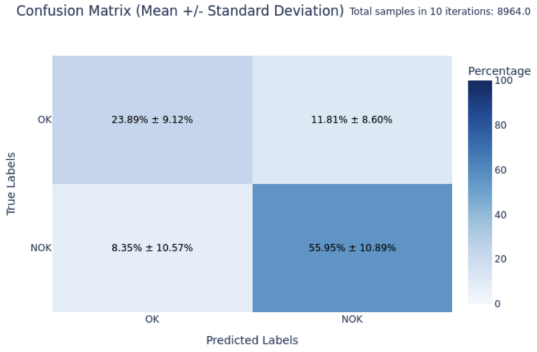

Fig. 9. DL Mean Confusion Matrix Test Set

B. Constrastive. Learning Model Performance

In contrast to the CNN approach, Contrastive Learning (CL) was explored through two main frameworks: a Siamese network and a SimCLR-inspired model. A total of 24 architectures were tested, each varying in convolutional layers (3 to 10), dropout rates, and pooling/normalization strategies. Although several configurations reached F1-scores above 0.60 on the main test set, many struggled to maintain consistency on the smaller gold standard of 60 images, occasionally overclassifying most coils into a single category (often NOK). This discrepancy exposed a key fragility: while certain setups excelled on the broader data, they did not necessarily translate their gains to more challenging borderline cases.

Deeper encoders generally extracted richer features,particularly from the original 264×18 matrices,yet simpler models(3 convolutional

layers) performed competitively when images were resized to 264×264. Normalization and pooling (whether partial or full) proved beneficial in stabilizing the learned embeddings, although Figure 10 and Figure 11 demonstrate that omitting these strategies usually led to noticeable performance drops. Dropout produced mixed outcomes: some architectures tolerated a 0.3–0.5 dropout well, while others showed better discrimination without it. Ultimately, the best CL models still lagged slightly behind the top CNN configurations when tested on the gold standard set, suggesting that further tuning through tailored augmentations or more robust embeddings,could help bridge the gap.

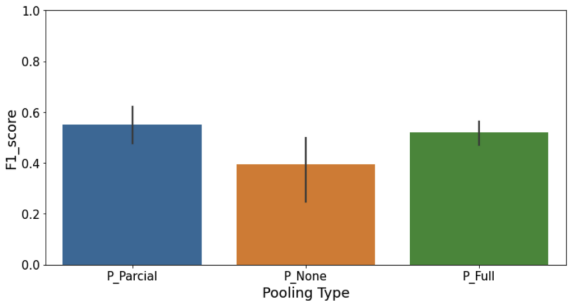

Fig. 10. CL Pooling Type

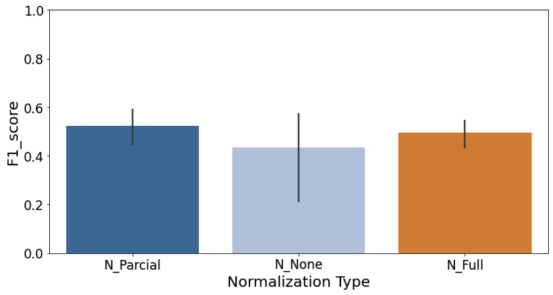

Fig. 11. CL Normalization Type

C. Comparative Analysis of CNN and Contrastive Learning

In evaluating zinc coating quality, CNNs consistently emerged as the stronger baseline. On the main test set, the best CNN achieved an F1-score between 0.89 and 0.93, with accuracy around 92–93%. Notably, its precision ranged from 90% to 94%, indicating a relatively low rate of false positives, while recall hovered between 88% and 92%. Inference times generally remained near 45 ms per image, which is suitable for near real-time inspection in industrial settings. However, performance did drop on the gold standard of 60 curated images, with F1-scores settling around 0.70–0.75. The primary cause of these misclassifications seemed to be the model's difficulty in distinguishing borderline defect cases, where slight deviations in zinc thickness could appear superficially similar to acceptable samples.

By contrast, Contrastive Learning (CL) methods—encompassing both Siamese networks and SimCLR-inspired frameworks demonstrated varying degrees of success. Some deeper architectures achieved test-set F1-scores exceeding 0.60 (and occasionally nearer to 0.66 when using 264×264 images), but a few runs overfit by classifying most samples as non-acceptable (NOK), thus inflating recall at the expense of precision. On the gold standard set, the stronger CL models posted F1-scores around 0.61–0.66, which fell short of the top CNN's performance. CL's main advantage lies in its ability to exploit unlabeled data by learning robust feature embeddings, but it proved sensitive to hyperparameters, such as dropout and normalization. Models that omitted pooling or normalization entirely tended to degrade more severely, underscoring the importance of architecture tuning.

Comparing their robustness to subtle defects illustrates a key distinction: while CNNs tended to balance precision and recall across most configurations, CL models sometimes excelled on one metric (often recall) by over-classifying coils into the NOK category. This imbalance suggests that while CL can capture complex visual patterns,particularly in data limited scenarios,it may be more susceptible to large errors if improperly calibrated. Furthermore, on borderline samples that required especially fine discrimination, CNNs generally maintained better F1-scores.

Thus, if abundant labeled data is available and real time performance is paramount, CNNs provide a more consistently accurate solution. However, when labeling resources

are limited, CL approaches potentially offer a way to leverage unlabeled examples for enhanced feature learning, albeit with a higher risk of unstable classification unless carefully tuned and augmented. Future research that integrates CL pretraining with CNN fine tuning alongside more sophisticated data augmentation, may help unify these strengths and address the challenges each method faces on subtle, borderline defects.

VI. Discussion

The experimental outcomes underscore the potential of advanced deep learning methodologies for automated zinc coating quality assessment. Specifically, the CNN-based approach demonstrated a strong capacity to handle large, well-annotated datasets, delivering high accuracy, precision, and recall on the primary test set. Its hierarchical feature extraction effectively isolated most defects, suggesting that, with sufficient labeled data, a well-designed CNN can robustly distinguish acceptable (OK) from non acceptable (NOK) steel coils. However, its performance drop on the gold standard subset of borderline samples indicates a lingering sensitivity to subtle thickness variations, suggesting that purely supervised methods may need additional fine-tuning or domain-specific data augmentation.

In contrast, Contrastive Learning (CL) showed promise in leveraging unlabeled data and learning richer, self-supervised embeddings. This characteristic is particularly attractive in industrial scenarios where labeling costs are high or defect types are highly imbalanced. Nevertheless, the study revealed that CL solutions can suffer from unstable classification, sometimes overemphasizing a single class to boost recall at the expense of precision. Additionally, CL's performance consistently lagged behind CNNs when exposed to the gold standard images, highlighting challenges in capturing borderline defects without extensive hyperparameter tuning or domain-tailored transformations.

Despite these distinctions, the overarching results indicate complementary strengths in both approaches. CNNs shine in well structured tasks backed by significant labeling efforts, while CL approaches facilitate robust representation learning in data limited environments. A particularly interesting avenue for future research may be to combine these paradigms. For instance, contrastive pretraining could create strong initial embeddings that a CNN fine-tunes on labeled data, potentially balancing the label efficiency of CL with the established supervised prowess of CNNs.

From a practical perspective, industrial stakeholders should carefully consider data availability, labeling resources, and the complexity of real-world defects when choosing an approach. CNNs offer consistent and often superior performance where ample labeled data can be secured, while CL excels in self-supervised feature extraction, albeit with a risk of instability if class distributions or defect variability deviate from training assumptions. In high throughput manufacturing contexts, inference speed becomes a deciding factor: our results confirm that CNNs can achieve near real-time performance (45 ms per image), though CL methods can be optimized with lighter encoders or more efficient augmentations.

Lastly, these findings align with broader Industry 5.0 goals, in which human expertise partners with automated intelligence to refine quality control processes. By positioning deep learning models as a tool rather than a replacement, human operators can focus on nuanced, high risk decisions, while the AI handles bulk classification. Integrating either approach into an agile, CRISP-DM informed workflow further allows iterative improvements as new defect classes arise or operating conditions shift.

Overall, this study underscores the value of advanced AI-driven inspection while illuminating key trade-offs between CNN based and contrastive learning based strategies. Going forward, more sophisticated data augmentation pipelines, hybrid model architectures, and real world pilot deployments will help clarify which combination of methods best addresses the persistent challenge of accurate, efficient zinc coating inspection.

VII. Conclusion

This paper has examined two major AI methodologies those are Convolutional Neural Networks (CNNs) and Contrastive Learning (CL),for automated quality assessment of zinc-coated steel coils. Our findings show that CNNs consistently achieve high performance when robust, labeled datasets are available, combining strong accuracy, precision, and recall with manageable inference times that suit real-time industrial inspection. However, like many fully supervised methods, CNNs faced challenges in classifying subtle or borderline defects within a smaller "gold standard" dataset, indicating that additional data augmentation or more refined network designs may be needed to handle ambiguous defect profiles.

By contrast, Contrastive Learning demonstrated a capacity to extract meaningful embeddings from limited or unlabeled data, an important advantage in scenarios where labeling every coil is impractical or expensive. Nevertheless, some CL models exhibited instability when tested on edge case samples, reflecting the heightened sensitivity of their performance to architectural tuning, data preprocessing, and balanced class distributions.

Overall, both approaches underscore the potential of AI driven quality inspection in accelerating and improving the detection of zinc coating defects. The choice between CNNs and CL ultimately depends on operational constraints including labeling resources, production timelines, and the severity of borderline defects. Future investigations may focus on hybrid solutions that combine contrastive pretraining with supervised fine tuning, aiming to unify the label efficiency of CL with the mature performance characteristics of CNNs. Ultimately, continuous integration of these approaches into real world manufacturing environments, supported by iterative refinements, can contribute significantly to the evolving landscape of Industry 5.0 quality control.

Acknowledgment

The Acknowledgement section of this manuscript discloses the funding sources. The two partial grants received had no financial impact, either positive or negative, on the public institutions as a result of the publication of this work.

- Ethics approval is not required for this study.
- Consent for publication was given by all the authors.
- Data and tools are available upon reasonable request.
- All authors contributed to the study conception and design.

The authors want to thank the EU RFCS research program for the support of this research through the grant ID 101034037 (DeepQuality project). First author and third want to acknowledge the partial support by the Spanish "Agencia Estatal de Investigación" through the grant PID2022-137748OB-C31 funded by MCIN/AEI/10.13039/501100011033 and "ERDF A way of making Europe".

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AI-Powered IT Infrastructure for Enhanced Safety in EAF Operations

Waseem Akram, Marco Vannucci, Arslan Siddique, Valentina Colla – Scuola Superiore Sant'Anna, Italy
Giovanni Bavestrelli, Alessandro Zamproni, TENOVA, Italy

This study addresses significant health and safety risks in steel industry Electric Arc Furnace (EAF) plants, such as extreme temperatures and toxic fumes. It proposes an advanced automated system utilizing IT and AI to enhance workplace safety through improved process monitoring and risk prevention. A primary goal is to minimize human presence near the EAF and detect hazards in real-time. This is achieved via an IT infrastructure integrating various sensors, including cameras and microphones, to continuously monitor the operational environment and provide data for AI analysis. The system uses computer vision and neural networks to identify early signs of incidents like smoke, flames, or abnormal furnace conditions. It also monitors worker presence, thereby significantly reducing accident risks. A camera-based prototype has been developed and tested, successfully identifying risk conditions and tracking personnel proximity to the EAF in real-time. The system will be improved in the future by refining detection accuracy, integrating additional sensor data, and expanding automation to further mitigate occupational hazards in steel production.

KEYWORDS: DIGITAL TRANSFORMATION, AI MONITORING, EAF SAFETY, STEEL PRODUCTION, ISTEEL-EXPERT

1. INTRODUCTION

Steel stands as a foundational material in contemporary society, indispensable for construction, manufacturing, and the development of infrastructures. However, the environments inherent to steel production including those involving Electric Arc Furnaces (EAFs), are characterized by significant hazards and operational complexities. Workers in these settings are routinely exposed to extreme conditions, including intense heat, toxic atmospheric emissions, and the pervasive presence of heavy machinery, all of which contribute to a heightened risk profile. Global data from 2022, encompassing 55 organizations representing 60% of World Steel members, reported 18.448 injuries and 90 fatalities among both employees and contractors. A significant portion of these incidents were attributed to slips, falls, and interactions with moving machinery, underscoring the persistent challenges in ensuring comprehensive workplace safety [1].

Specifically, EAF operations, while vital for steel recycling, present unique and severe safety risks, which stem from the inherent characteristics of the process, such as the powerful electric arcs, high voltage, and the generation of noxious gases, all of which necessitate stringent safety protocols and continuous vigilance.

The steel industry has proactively adopted a range of safety measures, including extensive training programs, advanced maintenance schedules, strategic operational guidelines, and the integration of automation for repetitive tasks, alongside regular updates to safety protocols. Despite these commendable efforts, a critical need persists for enhancing hazard identification methodologies [2]. A pivotal shift from predominantly manual to automated processes is essential to further mitigate human error and significantly improve the efficacy of safety interventions within steel mills. Automated systems offer a robust solution by continuously monitoring hazardous environments, thereby enabling the early detection of potential incidents. Artificial Intelligence (AI) plays a transformative role in this paradigm shift, providing sophisticated capabilities for real-time analysis, precise detection, and comprehensive surveillance. Furthermore, AI-driven data analysis systems contribute to operational cost reductions by automating tasks traditionally performed manually.

To directly address the minimization of human exposure within EAF environments and facilitating the rapid identification of hazardous situations, this research introduces EAFvision. EAFvision represents an advanced, automated pipeline specifically engineered for real-time safety surveillance. Its development involved the deployment of an integrated sensor system—comprising cameras, microphones, and other data-gathering

devices—at an active EAF facility. This infrastructure was meticulously designed to acquire specific datasets crucial for addressing diverse worker safety concerns. Leveraging these comprehensive datasets, we have developed and rigorously tested Computer Vision (CV) algorithms capable of detecting early indicators of incidents, such as the presence of smoke, flames, and abnormal furnace conditions. Crucially, EAFvision also incorporates solutions for real-time monitoring of worker presence, enabling the automatic cessation or modification of hazardous operations when personnel are detected within predefined critical zones. This approach significantly enhances situational awareness and operational safety, marking a substantial advancement in industrial hazard prevention.

This work addresses a notable gap in applying computer vision techniques to enhance EAF safety and efficiency. Unlike prior investigations, this research comprehensively evaluates diverse state-of-the-art object detection models for critical safety functions: personnel detection and acknowledgement of the early signs of fumes or flames emissions around the electrodes and roof which could be caused by an evolving dangerous reaction. By providing a detailed comparative analysis of model accuracy, inference speed, and deployment feasibility, these findings offer insights for developing robust, real-time monitoring systems poised to fundamentally improve safety protocols and optimize production workflows in demanding industrial settings.

2. THE OPERATIONAL ENVIRONMENT AND THE SAFETY CHALLENGES

The EAF constitutes a critical component within modern steel production, primarily facilitating the recycling of scrap metal into new steel. This process, while highly efficient and environmentally beneficial in terms of resource utilization, inherently operates under conditions that pose substantial and multifaceted hazards. The EAF environment is characterized by exceptionally high temperatures, frequently exceeding 1600∘C, which are necessary for melting scrap metal. These extreme thermal conditions not only present severe burn risks but also contribute to the degradation of equipment and the generation of intense radiant heat that can affect personnel working in proximity [3].

Furthermore, the EAF process involves complex chemical reactions that release various toxic emissions, including carbon monoxide, sulfur dioxide, and heavy metal particulates. Inadequate ventilation or accidental releases of these gases can lead to acute respiratory issues, long-term health complications, and even fatalities for exposed workers. The operational area is also dominated by heavy machinery, such as overhead cranes, charging buckets, and ladle cars, which are in constant motion. The movement of these massive components, often carrying molten metal or heavy loads, creates significant risks of crushing injuries, collisions, and material spills.

Beyond the inherent environmental dangers, the operational dynamics of an EAF introduce specific risk situations for both personnel and the overall process. Workers are frequently required to perform tasks in close proximity to the furnace, such as material charging, sampling, and refractory maintenance. These activities expose them to direct contact with extreme heat, molten splashes, and the potential for sudden, unpredictable events like arc flashes or explosions caused by moisture in the scrap. The presence of high voltage electricity, essential for generating the arc, adds another layer of grave danger, with the potential for severe electrical shocks. Moreover, operational hazards extend to the integrity of the process itself. Malfunctions in electrode movement, uncontrolled smoke or flame emissions, and anomalies in furnace conditions can escalate rapidly, leading to equipment damage, production downtime, and, critically, increased safety risks. The dynamic and often unpredictable nature of the EAF operation necessitates continuous, vigilant monitoring to detect deviations from normal parameters and to ensure the immediate implementation of safety protocols, thereby safeguarding both human life and operational continuity.

Traditional manual inspection methods, while foundational, possess inherent limitations in such dynamic and hazardous settings. Human observers are susceptible to fatigue, distraction, and the physical constraints of operating in extreme environments, which can lead to delayed detection or missed anomalies. Furthermore, the volume and velocity of operational data generated by an EAF make comprehensive real-time analysis by human personnel impractical. Consequently, there is a need for automated monitoring systems that can provide uninterrupted surveillance, process vast datasets instantaneously, and identify subtle deviations indicative of impending hazards, thereby overcoming the intrinsic limitations of intermittent human oversight.

To further enhance safety measures and enable efficient monitoring of critical operational processes within the

EAF environment, among other tasks, two key tasks were specifically designed, which were selected based on their importance and criticality concerning safety in an active EAF plant. They encompass the detection of personnel and the identification of smoke around the electrode. The subsequent subsections delineate these specific functionalities.

- **Person Detection.** A primary objective in developing CV systems for the EAF industry is to significantly augment worker safety within the facility. CV systems are instrumental in automatically triggering alerts when a worker is identified within a designated critical zone, thereby promptly notifying operators of a potential hazard. This single-class detection task provides continuous tracking of worker presence in real-time.
- **Smoke Detection Around the Electrode.** This task involves the continuous surveillance of emissions in the vicinity of the electrode to ascertain the presence of smoke and to identify unusually elevated smoke levels. The detection of such anomalies is crucial for recognizing irregularities in the EAF process. The system is engineered to generate immediate alerts upon the detection of dangerous smoke levels, enabling operators to initiate prompt responses and mitigate potential hazards. This classification task effectively discriminates between "smoke" and "no smoke" conditions.

3. A VISION BASED SAFETY MONITOR: ARCHITECTURE AND IMPLEMENTATION

The EAFvision system is built upon an integrated hardware and software infrastructure designed for continuous, comprehensive monitoring of the EAF process. This infrastructure leverages a diverse array of sensors strategically deployed throughout the EAF facility. Numerous high-resolution cameras are positioned at critical vantage points to capture visual data of the operational area, ensuring full coverage for tasks such as personnel tracking and anomaly detection. Complementing these visual inputs, an array of microphones is integrated to monitor acoustic signatures, which can indicate abnormal operational sounds or impending mechanical failures. Furthermore, thermal cameras are employed to provide critical temperature data, enabling the early identification of overheating components or uncontrolled thermal events that might not be visible to the naked eye.

All data streams from these sensors are seamlessly collected and centralized within a locally installed preprocessing unit. A dedicated, high-capacity database has been established to store this continuous influx of multi-modal data, ensuring efficient retrieval and processing for real-time analysis and historical review. For immediate operational awareness, a comprehensive dashboard provides real-time visualization of all monitored parameters and detected events. This intuitive interface allows operators to quickly assess the safety status of the EAF, view live feeds, and receive instant alerts. Beyond real-time consumption, the system is designed to facilitate data extraction for further analysis, reporting, or integration with other enterprise systems through a well-defined Application Programming Interface (API), ensuring flexibility and interoperability.

Data collection

This comprehensive IT framework serves as the foundation for collecting the extensive datasets essential for training and validating EAFvision's classification and object detection models. The continuous streams of images and video frames captured during actual EAF production, reflecting a wide range of operational conditions and safety-critical scenarios, was used to create this dataset. In this dataset, each image and video frame related to the considered tasks underwent meticulous manual annotation, a vital step that labels specific elements relevant to safety and operational efficiency, such as personnel, smoke, and furnace components. These annotated data are then systematically utilized for training and evaluating the various computer vision models, ensuring that the AI algorithms are robustly prepared to identify hazards and support real-time decision-making in the EAF environment. At the end of the data gathering process, the datasets available for training and validating the models were composed of:

- more that 3000 individual images to be used for the human presence detection task;
- more than 500 images to be used for the smoke detection task.

The dataset is rigorously partitioned into training, validation, and test sets for each specific task, guaranteeing comprehensive model development and an unbiased assessment of performance.

4. IMPLEMENTATION AND APPLIED RESULTS

4.1 Tested models

To ensure EAFvision delivers highly reliable and efficient real-time safety monitoring, a thorough evaluation of various advanced machine learning models was conducted. The selection of these models was driven by their proven capabilities in object detection and classification, with a particular emphasis on performance in demanding industrial environments where both speed and accuracy are fundamental. Our objective was to identify the most suitable algorithms that could effectively process visual data from the EAF, enabling rapid identification of safety-critical events.

Object detection models, which are central to EAFvision's capabilities, generally fall into two main categories: two-stage and single-stage detectors. Two-stage detectors, such as Faster R-CNN [4], Mask R-CNN [5], and Cascade R-CNN [6], operate by first identifying potential areas where an object might be located (known as *region proposals*) and then performing a more detailed analysis to classify and refine these detections. While highly accurate, this sequential approach can sometimes be slower. In contrast, single-stage detectors process the entire image simultaneously to detect and classify objects. This integrated approach typically makes them significantly faster, a crucial advantage for real-time applications where immediate responses are necessary.

Among the single-stage detectors, the You-Only-Look-Once (YOLO) [7] family of models has gained substantial recognition for its exceptional real-time detection capabilities. Given their widespread success and efficiency, our experiments included an extensive range of recent YOLO iterations, specifically YOLOv8, YOLOv9, YOLOv10, and YOLOv11. The goal was to meticulously compare their performance on our EAF-specific datasets to pinpoint the optimal balance of speed and accuracy for our application. Additionally, other notable single-stage detectors were considered, such as RetinaNet [8], which is designed to achieve a strong balance between detection speed and precision through its unique architecture.

More recently, a new class of models known as Transformers has emerged, offering a powerful alternative for analyzing visual data. These models excel at understanding global context within an image, a capability that can be highly beneficial for complex industrial scenes. We investigated models like DEtection TRansformer (DETR) and its real-time counterpart, RT-DETR [9], in particular, has demonstrated impressive advancements in addressing speed and efficiency challenges by optimizing its internal mechanisms while maintaining high detection accuracy. Our comprehensive testing included training and evaluating these Transformer-based models against our EAF datasets, allowing for a detailed performance comparison with the established single-stage and two-stage detectors. This rigorous evaluation process was fundamental in selecting the most effective models for integrating into the EAFvision pipeline.

4.2 Experimental set-up

Model evaluation involved rigorous experiments assessing performance within the EAF environment. We trained various YOLO models (v8-v11) and RT-DETR, alongside RetinaNet, Mask R-CNN, Faster R-CNN, and Cascade R-CN. All models were trained and evaluated on the dataset previously described according to the predefined partition into training, validation and test images.

Experiments utilized a high-performance Ubuntu system with an NVIDIA GeForce RTX 3090 GPU and 128 GB RAM, ensuring efficient training and inference. Python 3.10.5 and PyTorch 2.5.1 supported YOLO model development, while Detectron2 models used Python 3.9.21 and PyTorch 2.5.1+cu121 with CUDA.

Object detection performance was quantified using mean Average Precision (mAP), precision, recall, and F1 score. Accuracy served as the primary metric for classification tasks. These standardized metrics ensured objective assessment of each model's effectiveness in EAF safety challenges.

5. RESULTS AND DISCUSSION

5.1 Person detection task

The main objective of this task is to ensure the safety of workers operating in high-risk zones within the EAF facility. As detailed in Table 1, the YOLOv9s model consistently demonstrated robust performance for person detection. It achieved a mAP50 of 0.96, complemented by precision and recall scores of 0.94 and 0.89, respectively. These results underscore the model's high reliability in accurately identifying personnel even

within challenging industrial environments, rendering it very suitable for safety-critical applications where both rapid and precise detection are indispensable.
Regarding inference time, as shown in Table 2, YOLOv9s exhibited very good efficiency, processing each image in approximately 9.8 milliseconds, which is crucial for enabling real-time detection capabilities. While RT-DETR-L (22.2 ms) and RT-DETR-X (28.4 ms) also demonstrated commendable precision and recall, their comparatively slower response times could potentially impede their effectiveness in urgent scenarios demanding immediate action. Furthermore, two-stage detectors, such as Cascade R-CNN, Faster R-CNN, and Mask R-CNN, generally presented slower inference times and lower precision compared to the YOLO models. Consequently, these models are less optimal for real-time applications in safety-critical industrial settings. Given its superior balance of accuracy and speed, YOLOv9s emerges as the most effective choice for person detection within the EAF operational context.

Table 1 Performance achieved on person detection task

Type	Model	mAP50	Precision	Recall
Two stages	Cascade R-CNN	0,86	0,45	0,54
	Faster R-CNN	0,9	0,47	0,56
	Mask R-CNN	0,76	0,31	0,44
Single stage	YOLO v11s	0,96	0,94	0,88
	YOLO v10s	0,95	0,94	0,88
	YOLO v9s	**0,96**	**0,94**	**0,89**
	YOLO v8s	0,95	0,9	0,88
	RetinaNet	0,93	0,49	0,58
	RT-DTER-1	0,95	0,94	0,91
	RT-DETR-x	0,96	0,91	0,92

Table 2 Inference time for the person detection task

Type	Model	Inference time (ms)
Two stages	Cascade R-CNN	16,6
	Faster R-CNN	25,5
	Mask R-CNN	21,4
Single stage	YOLO v11s	5
	YOLO v10s	6,1
	YOLO v9s	**9,8**
	YOLO v8s	3,9
	RetinaNet	11,8
	RT-DTER-1	22,2
	RT-DETR-x	28,4

5.2 Smoke detection task

For the task of smoke detection, which primarily involves classifying the presence or absence of smoke rather than identifying specific bounding boxes, the YOLOv11s model was employed as a classification model. This

model achieved an Accuracy of 93%, indicating a strong capability in accurately identifying smoke within the EAF environment. While this performance is highly promising for real-world application, continuous efforts to further enhance accuracy remain vital, particularly in critical industrial settings where the early and reliable identification of hazards is paramount.
The model's overall performance is further reflected by its Fitness score of 0.9627. In the context of YOLO models, the *Fitness score* is a comprehensive metric that combines various performance indicators (such as precision, recall, and mean average precision) into a single value, providing an aggregated measure of how well the model is performing across its objectives.

Table 3. Performance on the smoke detection task

Model	Accuracy	Fitness
YOLO v11s	0,93	0,96

6. CONCLUSIONS AND FUTURE OUTLOOK

In this paper, EAFvision was introduced as a comprehensive pipeline for evaluating and fine-tuning state-of-the-art computer vision models specifically for safety-critical detection tasks within the EAF steelmaking use case and the results of exploratory experiments is presented and discussed. These initial experimental results showed that YOLO models, particularly YOLOv9s, overcome the other evaluated architectures in terms of precision, recall, and inference speed. YOLOv9s proved to be the optimal selection for critical tasks such as personnel detection and smoke detection in the context of this first session of experiments. Through comparative analysis with models including YOLOv8, RT-DETR, and various two-stage detectors, it was established that YOLO models offer a good combination of high accuracy and rapid processing, rendering them well-suited for real-time industrial applications. Notably, YOLOv9s performs well in detecting personnel in hazardous zones, thereby facilitating swift responses to prevent potential accidents. Nonetheless, the research is still in an exploratory stage and further investigations are being conducted on the topic by also exploring other AI algorithms. Once the investigation is completed, the best performing model will be transferred to the production stage.
This exploratory study underscores the transformative potential of advanced AI and CV technologies in significantly enhancing both safety protocols and operational efficiency within the steel manufacturing sector. Future research endeavors will concentrate on further optimizing these systems and extending their capabilities to encompass additional critical safety tasks, with the ultimate aim of realizing fully automated, intelligent monitoring solutions for steel production environments.

ACKNOWLEDGMENTS

The work described in the present paper has been developed within the project entitled "*Remote expert virtual system enhancing human management capabilities and favors preservation, transfer and continuous evolution of knowledge for steelmaking operations*" (Ref. iSteel-Expert, Grant Agreement No. 101112102) that has received funding from the Research Fund for Coal and Steel of the European Union, which is gratefully acknowledged. The sole responsibility of the issues treated in the present paper lies with the authors; the Commission is not responsible for any use that may be made of the information contained therein.

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Seamless Quality Management in the Transition to Energy-Efficient Steel Production

Thorsten Claff, Dr.-Ing. Michael Raus – QuinLogic GmbH, Germany

This paper explores how a quality execution system effectively addresses the key challenges of the "twin transition" – the shift toward ecological and digital sustainability – making these transformations more manageable. As steel manufacturers move to more energy-efficient production and replace plants, consistent quality control becomes increasingly complex. In this rapid transformation, driven by ecological demands and digitalization, a quality execution system plays a pivotal role. Designed for flexibility, it adapts to changing processing routes while ensuring reliable quality management. When processing routes change, impacts extend beyond data: product flow and genealogy must be remodeled, product quality reassessed, and quality processes realigned. New causes of deviations must be analyzed and documented, while surface defects require evaluation that exceeds previous standards. A quality execution system is uniquely equipped to meet these challenges. By integrating advanced production data warehousing, monitoring, surface defect analysis, automated grading, and root cause analysis, it enhances production accuracy, reduces rework, and improves plant efficiency. These capabilities provide deep quality insights, helping manufacturers adapt to supply chain changes while maintaining consistent product quality – even as raw materials and energy sources shift toward sustainable alternatives.

KEYWORDS: TWIN TRANSITION – PRODUCT QUALITY – QUALITY EXECUTION SYSTEM – PRODUCTION DATA WAREHOUSE – SURFACE INSPECTION DATA

INTRODUCTION: THE PRESSURES OF THE TWIN TRANSITION

The global steel industry is at a pivotal crossroads, shaped by the urgent need to decarbonize and modernize simultaneously. This dual challenge, often described as the twin transition, demands both ecological transformation – through energy-efficient, low-emission processes – and digital transformation, encompassing automation, data integration, and intelligent systems. Together, these transitions are not only redefining the technological landscape of steel production but also deeply influencing how quality is managed across increasingly complex value chains.

As plants implement new technologies such as hydrogen-based steelmaking, direct reduced iron (DRI), and electric arc furnaces (EAFs), the traditional assumptions underpinning quality control are being disrupted. At the same time, the shift to digital workflows and connected systems opens new opportunities to reimagine quality assurance as a dynamic, responsive, and data-driven function. This paper explores how a modern Quality Execution System (QES®) addresses the challenges of the twin transition by enabling flexible, robust, and actionable quality management across changing production conditions.

REDEFINING QUALITY IN A CHANGING PRODUCTION LANDSCAPE

The shift to energy-efficient steel production is not merely a matter of replacing one technology with another. It involves reconfiguring entire production routes, altering the sequence and nature of processing steps, and in some cases, decentralizing operations that were previously linear and monolithic.

For example, a plant transitioning from blast furnace-basic oxygen furnace (BF-BOF) production to electric arc furnace (EAF) steelmaking may experience profound changes in material input, thermal behavior, and surface characteristics. Additionally, new production modules – such as hot briquetted iron input, preheating units, or novel descaling technologies – introduce variables that affect quality outcomes in previously unknown ways.

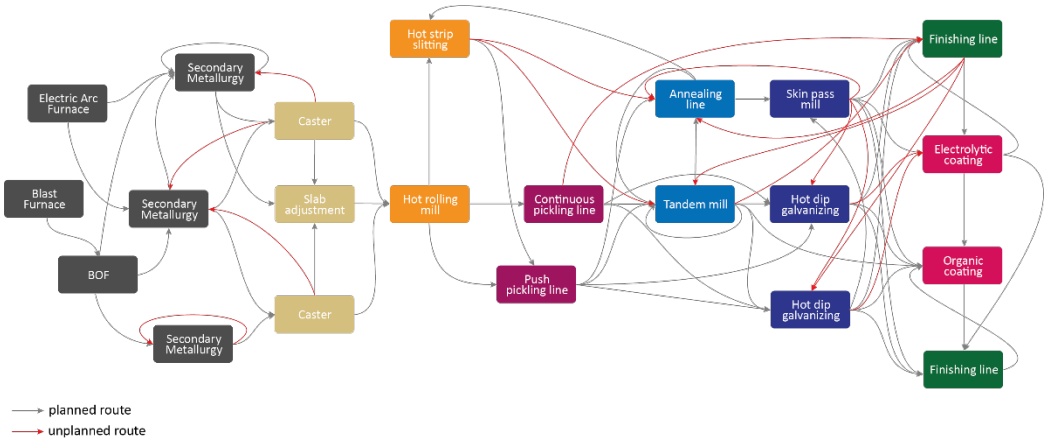

Fig.1 – Every change to the production landscape results in new/modified process routes, which can have an impact on process and product quality.

In such an environment, static quality rules, rigid inspection workflows, and isolated data silos are insufficient. A successful quality execution strategy must adapt dynamically to evolving product flows, while preserving traceability, consistency, and speed in quality decision-making. The QES® emerges as the central enabler of this adaptability.

THE ROLE OF THE QUALITY EXECUTION SYSTEM

A Quality Execution System is a software platform that integrates quality data, product tracking, inspection outcomes, and decision rules across the entire production process. It does not operate in isolation but acts as a vital link between Manufacturing Execution Systems (MES), surface inspection systems, and production databases. In the context of the twin transition, QES® plays a crucial role by ensuring adaptability to changing processing routes, unifying and visualizing diverse data sources, and enabling automated quality control.

As processing paths evolve, QES® reconstructs the genealogy of each product unit by a complex genealogy modeler, maintaining uninterrupted traceability and preserving the contextual integrity of defect data, even when process steps are added, removed, or modified.

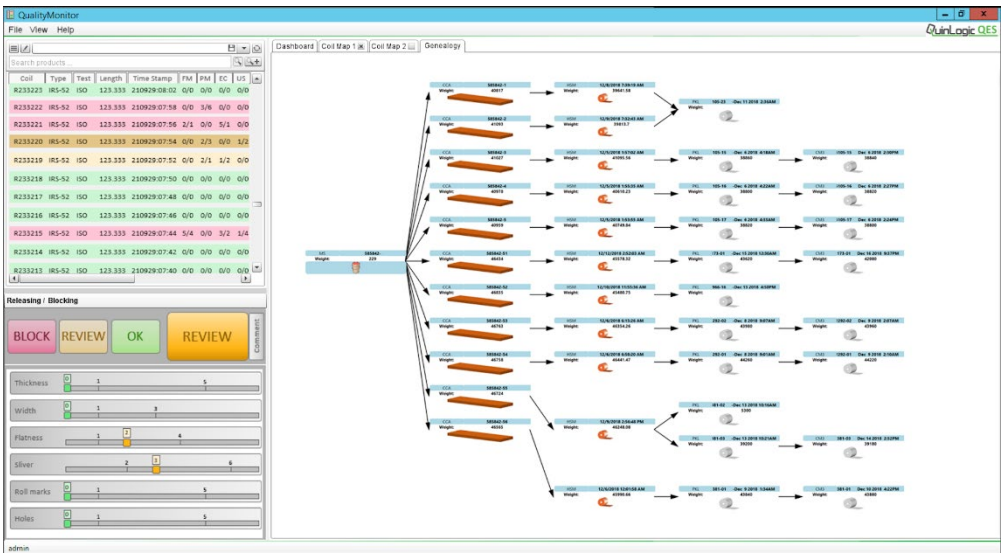

Fig. 2 – The QES® user interface (QualityMonitor) shows the genealogy graph for each production and location. It is interactive and allows to switch to each product or product stage for detailed information and analysis.

At the same time, it consolidates inspection and process data into a coherent model that supports clear visualizations. These visual insights help operators understand the condition of individual coils and detect broader trends across product families or campaigns, even when coils follow varying equipment combinations.

In addition, the system uses customizable rule sets to automatically assign grades, trigger rework actions, or highlight anomalies for further investigation. This level of automation is essential for managing large volumes of data in real time and for ensuring that quality remains consistent, even as production conditions and routes change rapidly.

ADVANCED SURFACE DEFECT MANAGEMENT

One of the most critical areas in steel quality control is surface inspection. In energy-efficient processes, surface behavior can change significantly due to factors such as altered heating cycles, new descaling methods, or increased variability in raw materials. As a result, managing surface defects becomes more complex and more important than ever.

QES® enhances surface inspection capabilities by dynamically mapping defects with precise spatial positions on the product and linking them to their full process history. This creates a high-resolution view of how defects relate to upstream events, helping to uncover their true causes. The system's built-in analytics can then process this information further by grouping related defects into clusters, detecting long defects, and distinguishing isolated anomalies from recurring patterns. This makes it much easier for operators to pinpoint the root causes of defects and take targeted corrective actions.

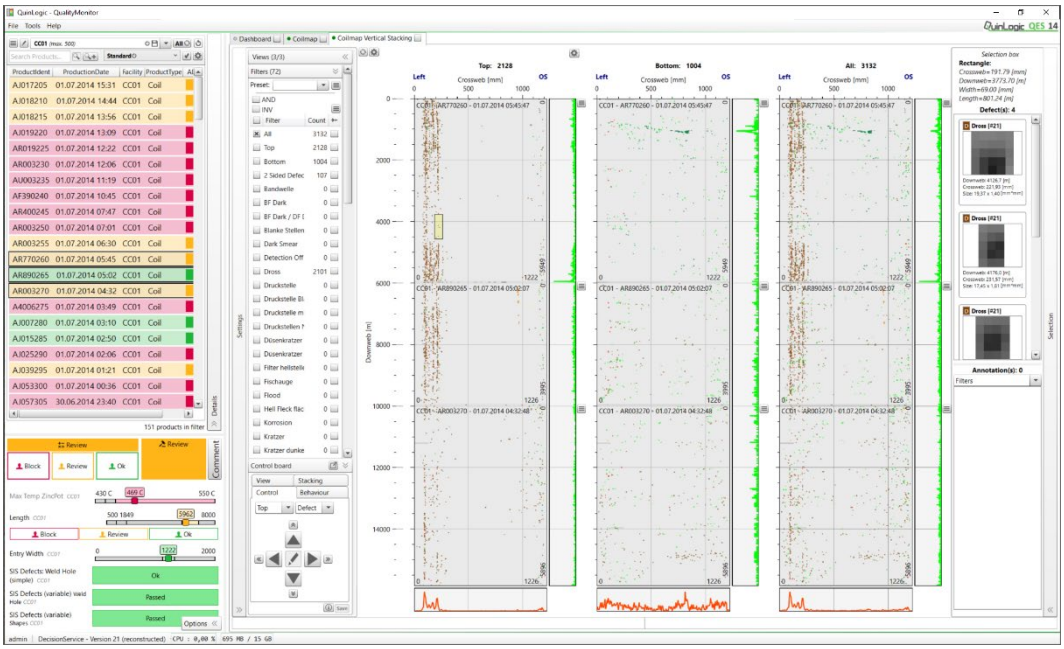

Fig. 3 – The QES® QualityMonitor contains a powerful surface inspection data application that goes far beyond the features of standalone surface inspection systems such as horizontal/vertical stacking, build-in postprocessing algorithms, geometric annotations and comparison of coil maps from different process stages.

Additionally, QES® uses predefined thresholds and business rules to automatically assign grades to products or recommend rework steps (see figure 3, left). It can also feed this information back to process controllers or maintenance systems, ensuring that inspection results directly inform process adjustments and help maintain a continuous quality feedback loop.

REALIGNMENT OF QUALITY PROCESSES

As production conditions shift, it is not enough to adjust inspection methods alone; entire quality processes must be reconsidered, from specification interpretation to root cause analysis. A robust quality execution system supports this realignment by enabling the rapid reassessment of quality criteria, as tolerances that were once acceptable may need to be tightened or relaxed when new processes result in different defect profiles.

The system allows these criteria to be reconfigured quickly and without downtime. It also ensures traceability across variable production routes by maintaining logical product flows even when physical paths change, which is essential for certification, customer confidence, and internal audits.

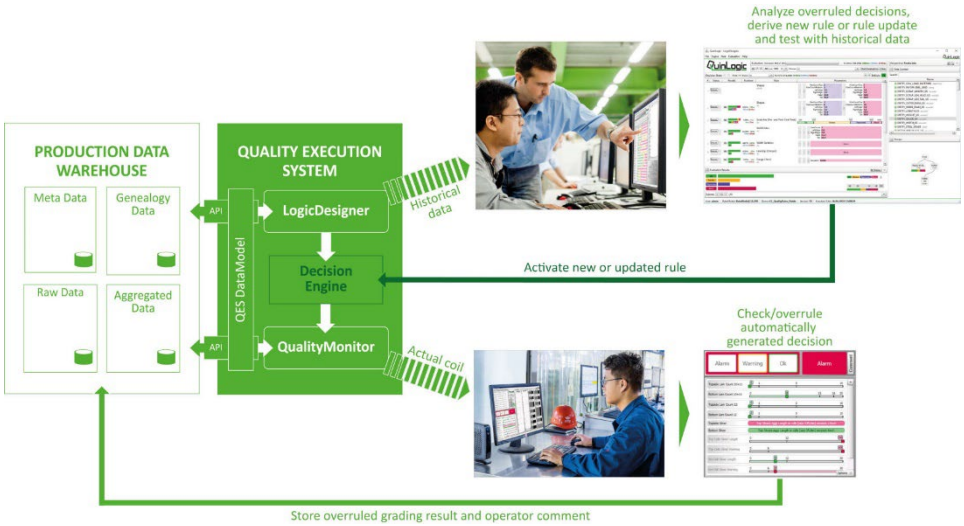

Fig. 4 – The work-sharing QES® process for optimizing the accuracy of the product grading can be repeated continuously and thus leads to a continuous improvement of the rule set of rules. This is especially useful and efficient when processing routes change, and the quality rules have to be adapted.

Intelligent alerting and reporting functions provide custom dashboards and early warnings so that quality deviations are detected promptly and understood in context. This means operators are informed not only about what has happened, but also about the likely reasons behind it, enabling faster and more effective intervention.

ROOT CAUSE ANALYSIS AS A DRIVER FOR FASTER IMPLEMENTATION

Decarbonization and the associated introduction of new production technologies fundamentally change how quality deviations arise. Unknown or unexpected defects may occur, caused by new raw materials, modified heating profiles, or unfamiliar equipment behavior. In this context, identifying the true causes of defects quickly and accurately becomes critical for minimizing costly trial-and-error loops and ensuring that process changes reach their full potential without compromising product quality.

Root cause analysis is therefore not just a troubleshooting tool but a strategic enabler for accelerating the transition to greener steelmaking. By systematically linking defect data with upstream process parameters, operators and engineers gain fact-based insights that allow them to adapt production steps more effectively and refine quality rules with each new learning cycle.

This is where the QES® DataCorrelator plays a central role. As an integrated analysis tool within the QES®, it can correlate vast amounts of production and inspection data to detect hidden patterns and dependencies that would be hard to identify manually. The DataCorrelator highlights correlations between process conditions and defect occurrences in clear visualizations, making it much easier for teams to pinpoint root causes, test corrective actions, and validate results rapidly.

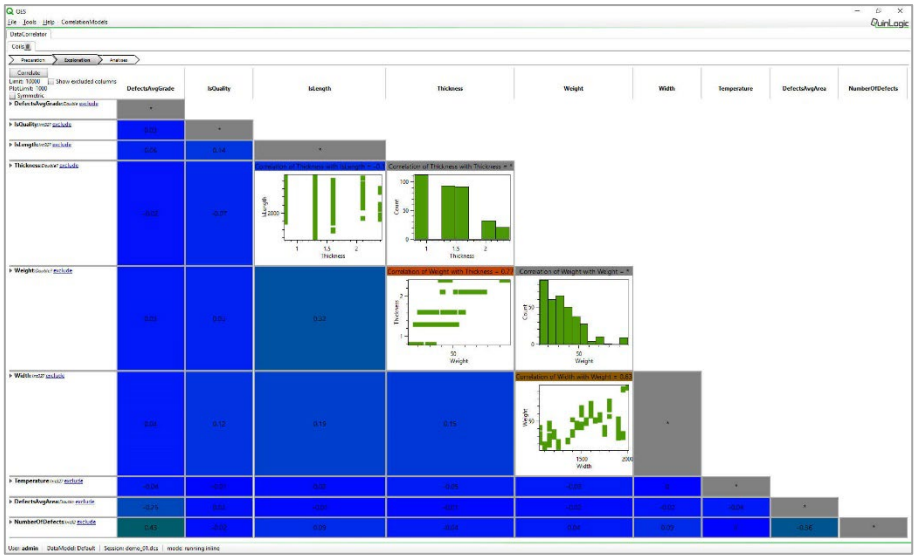

Fig. 5 – The QES® DataCorrelator tool is specifically designed for process and quality experts without specialized knowledge in data analysis. It enables correlations between parameters and data from the entire process chain and from all measuring systems to be uncovered and used for quality predictions.

By shortening the time needed to understand new quality issues and by automating parts of the correlation work, the DataCorrelator helps customers speed up the implementation of process changes that are vital for decarbonization. In doing so, it ensures that new technologies do not introduce unpredictable quality risks but instead contribute reliably to the sustainability and competitiveness of steel production.

USABILITY AND HUMAN INTERACTION

In times of transformation, human-machine collaboration becomes even more vital, requiring systems that are not only powerful but also intuitive to use. The Quality Execution System addresses this need by offering configurable interfaces that allow operators to customize dashboards according to their tasks, whether they are reviewing coil histories, tagging defects or launching investigations.

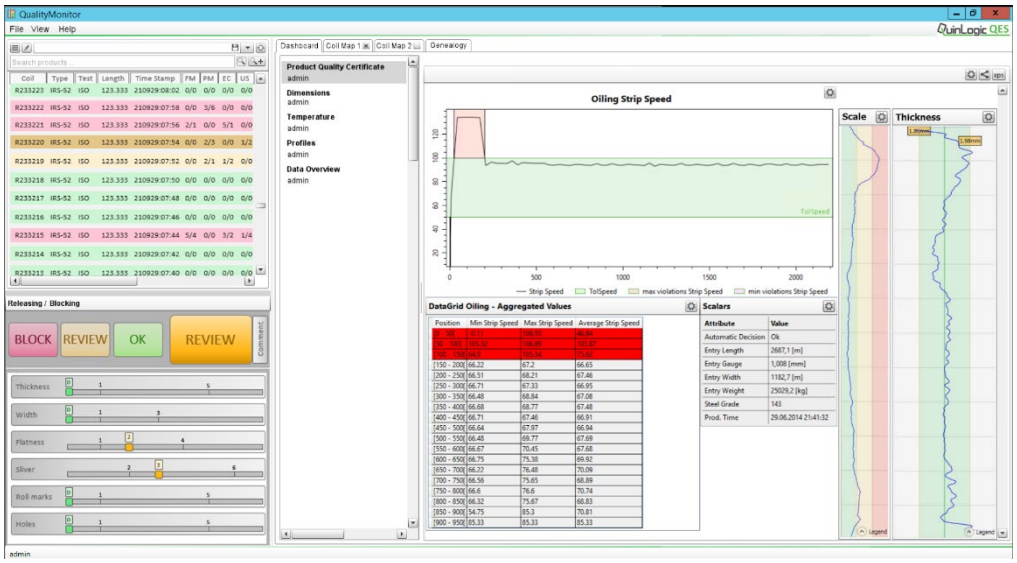

Fig. 6 – The QualityMonitor dashboard gives operators a customizable view of key quality and production data. Tables, interactive charts and other media support quick decisions, and virtually any number of dashboards can be created and printed as certificates and reports.

Guided interaction features, such as defect tagging, visual analytics for periodic defect detection and interactive genealogy maps, help reduce complexity and shorten training times. In addition, seamless integration with external systems ensures that the QES® can receive instructions from ERP systems and send reports to external quality portals, acting as an open platform that connects all relevant data streams within the digital enterprise.

PROACTIVE APPROACH FOR A SMOOTH TRANSITION

Successfully managing the twin transition in the steel industry requires much more than simply adopting new technologies or production methods. It demands a robust foundation of reliable, connected, and well-structured data. Without this foundation in place beforehand, the introduction of new production routes, such as hydrogen-based steelmaking or DRI, can create data silos, gaps, or inconsistencies that undermine quality assurance from the start.

A modern Quality Execution System relies on clean, comprehensive data streams to monitor product genealogy, track process deviations, analyse root causes, and adapt quality criteria dynamically as conditions change. If this data infrastructure is missing or fragmented, these critical functions either cannot be used effectively or require significant retrofitting later – often at a much higher cost and with potential risks for production continuity.

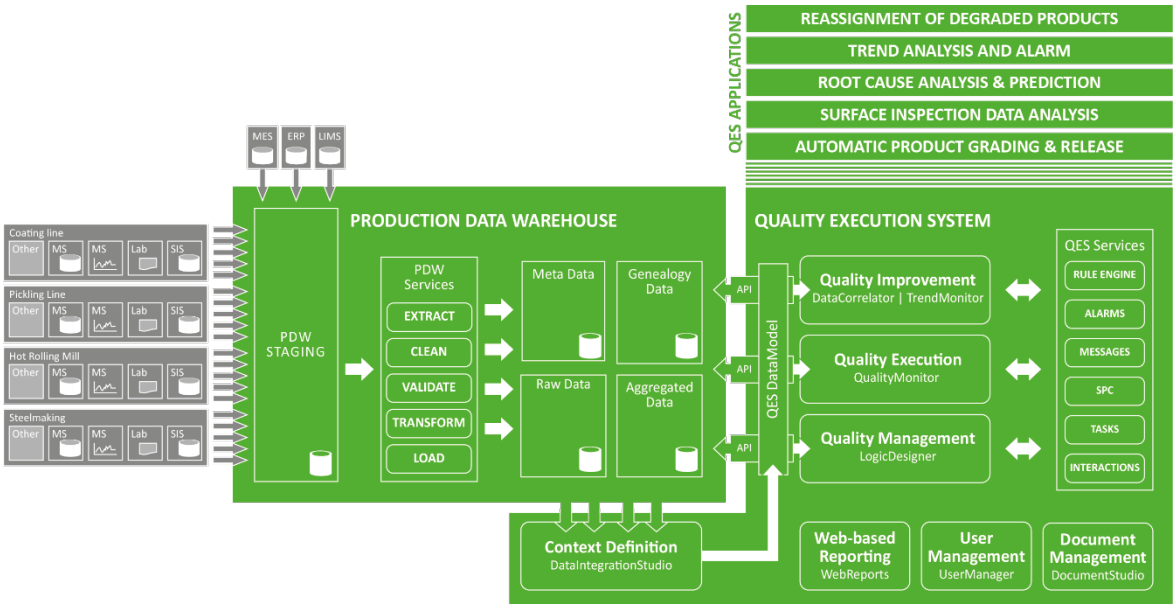

Fig. 7 – Only a mutually optimized system of production/quality data infrastructure and quality execution functionality meets the challenging requirements of twin transition. The QuinLogic Production Data Warehouse was specifically designed and developed for the requirements of the Quality Execution System (QES®).

Establishing a well-designed data architecture and deploying a QES® early provides a stable backbone for integrating new technologies into the existing production ecosystem. It ensures that when the actual process changes begin – such as commissioning new hydrogen lines or connecting ERP and MES systems – there is already a trusted quality layer in place that can capture, contextualize, and process data in real time.

This proactive approach transforms quality management from a reactive cost factor into a strategic asset that supports a smooth transition. It allows steelmakers to identify and address quality risks before they escalate, shorten ramp-up phases for new processes, and build customer confidence by demonstrating that quality standards are safeguarded during every stage of transformation.

In short, setting up a solid data infrastructure and a flexible Quality Execution System in advance lays the groundwork for a resilient, future-proof quality strategy — making the complex path of decarbonization and digitalization not only manageable but also a catalyst for sustainable, profitable growth.

CONCLUSION: BUILDING QUALITY RESILIENCE

In the age of the twin transition, the steel industry must embrace tools that are as dynamic and intelligent as the changes it faces. The proven Quality Execution System (QES®) enables this by embedding adaptability, automation, and deep insight into the core of quality management.

By supporting changing production routes, enhancing surface defect detection, and improving human interaction with complex data, the QES® ensures that quality is not a casualty of transformation but rather a driver of it. It bridges the gap between production reality and quality requirements, making it possible to react to new process variables swiftly and consistently, while maintaining the high standards that customers demand.

Beyond technical capabilities, the real strength of QES® lies in how it turns data into actionable knowledge. Vast streams of production and inspection data tell the story of each product; the QES® writes the solution by translating this story into concrete quality decisions, automated controls, and continuous improvement actions.

In a market shaped by decarbonization, digitalization, and evolving customer expectations, this ability to learn and adapt continuously is not optional – it is essential for staying competitive and profitable. By investing in a solid data infrastructure and a future-proof QES® early on, steelmakers gain the strategic advantage they need to safeguard quality today and secure success tomorrow.

TRANSPARENT ONLINE CALCULATION OF PRODUCT CARBON FOOTPRINT IN STEEL INDUSTRY

Martin Schlautmann[1], Heinz-Josef Ponten[1], E. Anouk Stigter[2]

[1]PSI Software SE, Parsevalstraße 7a, 40468 Düsseldorf, Germany
[2]Tata Steel in IJmuiden, PO Box 10.000, 1970 CA IJmuiden, The Netherlands

Reliable carbon footprint calculations and certificates for the various steel products are increasingly demanded by the market. A production management system allows to track the material and energy consumptions for each piece of produced material. Thus, it is able to transparently calculate the related greenhouse gas emissions on piece and product level, along the entire production chain from raw material preparation and processing in iron and steelmaking, via hot and cold rolling to commissioning for shipment after finishing lines, i.e. from cradle-to-gate. By configuration of process characteristics impacting the product carbon footprint and corresponding greenhouse gas emission factors as well as calculation rules for the resulting emissions, the presented solution can be adapted to the granularity of available process data in a steel plant. It is possible to define different emission values for each produced material like gross values including scrapped parts of a material, net values without such scrapped parts or the resulting class of green steel according to the recently published Low Emission Steel Standard. Thereby, a steel plant can start with implementation of a product carbon footprint tracking based on mass balances and produced material weights in defined plant areas. In a next step, if relevant process data are available and considered on the level of single production steps, the accuracy of emission calculations is increased accordingly for the related product. This procedure is exemplified by the implementation of a product carbon footprint tracking at Tata Steel in IJmuiden within PSImetals production management system.

KEYWORDS: PRODUCT CARBON FOOTPRINT, CRADLE-TO-GATE TRACKING, PRODUCTION MANAGEMENT, DECARBONIZATION

INTRODUCTION

The steel industry, accounting for 7-9% of the global anthropogenic greenhouse gas (GHG) emissions [1], plays a pioneering role in the currently ongoing transformation towards sustainability by replacing fossil reduction agents and energy carriers with renewable ones, e.g. green hydrogen and electricity. Modern production management systems (PMS) have to track and calculate all necessary process data to support the decarbonization journey of metals producers in the fields of production planning, scheduling and execution.

Steel industry customers, like automotive manufacturers and construction companies, are increasingly asking for CO_2 reports of ordered goods. Thus, steel producers need to transparently calculate and track greenhouse gas (GHG) emissions on a product level, along the whole production chain. This includes preparation and charging of raw materials, the different production steps in iron and steelmaking, casting, rolling and finishing up to the commissioning of the final products for shipment, i.e. from cradle to gate. This paper presents an approach for transparent online cradle-to-gate calculation of product carbon footprints (PCF) integrated within a quality management component of a manufacturing execution system (MES) for metals producers. It tracks all required information for accounting of GHG emissions, both per production step and aggregated over all steps until shipment. Depending on the granularity of available process data in a steel plant, the PCF calculations can be adapted in order to take into account as much individual consumptions of material and energy with related GHG emissions per production step as possible. Such a system is able to overcome the shortage of current mass based CO_2 reporting aggregated on the company level, that is the corporate carbon footprint (CCF).

Specifications like the Greenhouse Gas Protocol Corporate and Product Standards [2],[3] and the international norm ISO 14067[4],[5] define requirements and guidelines to quantify greenhouse gas emissions on product level. Recently, the German Steel Association published the Low Emission Steel Standard (LESS) aligned with the international standards to categorize products within an emission classification system and to promote the national as well as European implementation of the concept of green lead markets as a climate protection instrument [6].

Three scopes have been defined for the tracking of GHG emissions:

- Scope 1 comprises emissions directly produced by processes in an organization,
- Scope 2 includes indirect emissions from consumed energy provided by an external supplier
- Scope 3 contains emissions related to any other indirect upstream emissions from purchased goods, as well as downstream emissions from distribution, usage and disposal of sold products.

PCF tracking is the basis for:

- green key performance indicators (KPIs) to be used to optimize production planning, scheduling and execution through weighted trade-off with classical economic KPIs (like throughput, costs and meeting delivery dates)
- green lead markets fostering the decarbonization journey of the industry through dedicated increase in demands for green steel [6].

PRODUCT CARBON FOOTPRINT TRACKING BY MES

MES Production Tracking

Comprehensive manufacturing execution systems, for steel production, supervise and track all events during production of a certain product and store all:

- related process data, i.e. consumed raw materials, electrical energy, chemical energy carriers (e.g. solid carbon carriers, liquid fuels, natural gas, hydrogen), oxygen, nitrogen, inert gas and other auxiliaries as well as durations and conditional parameters of each process step (e.g. heating with electrical power, deep vacuum treatment with vessel pressure, stirring with inert gas flow rate, …)
- relevant product quality data, e.g. chemistry, hardness, tensile strength, geometry, flatness.

These data are received based on related events or cyclically along the time axis. The cyclic data are typically measured or calculated by level 1 and 2 process control systems and reported to the MES. This allows the monitoring of the information in real time and creation of performance reports or evaluations based on historic data. The MES tracking functionality is the basis for optimized production in regards to adjustment of targeted product quality with minimum material and energy consumption (i.e. costs) and/or maximum productivity (in terms of yield and production time). The transformation of production towards decarbonization of all involved processes also requires tracking of GHG or CO_2 equivalent (CO_2e) emissions related to the different process steps and their energy and material consumptions per piece of product, i.e. PCF tracking.

Product Carbon Footprint Tracking

Product Carbon Footprint data can be treated like quality data, it may be checked against tolerances during the production process and included into the product certificate. Thus, technologies developed for quality management within production management systems are ideally suited to handle PCF data. An example is the “Quality Process Snapshot” within PSImetals [7], which collects, in real time, and stores:

- all process and material data relevant for the carbon footprint of a material piece at a certain production step (like material, electrical energy and process gas consumptions, offgas volume and analysis, slagged material, cut scrap parts) as provided by standard production report messages,

- as well as the derived product carbon footprint from this step and aggregated over all steps so far (cf. Fig. 1).

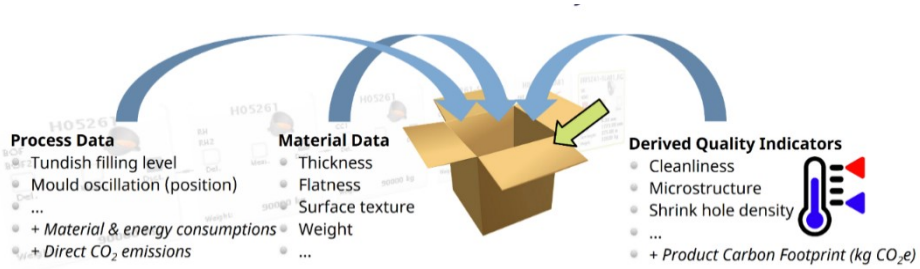

Fig. 1 - PSImetals Quality Process Snapshot

The stored data is linked to the “material genealogy” nodes related to the respective production steps. The material genealogy is used by various functions within PSImetals quality management with the main purpose, which is rather evident in the name, being to answer questions like:

- How is a material composed of materials of a former production step?
- Which materials include parts of a former material?
- What are the material characteristics of a former material piece?
- Which material defects exist for a former material piece?
- Where was a material defect located within a material of a former production step?

Another question in the context of decarbonization to be answered by the material genealogy is:

- How is the PCF of a material evolving along the history of its production, i.e. along its material genealogy?

To enable the answers to such questions, requires the tracking of all processes and related data which influence the materials genealogy (melting, refining, casting, rolling, welding and cutting processes, scrap cuts, sample cuts, number of passes, coiling processes changing coil orientation). PSImetals keeps track of this as well as of the related geometric, physical and chemical material characteristic changes – including related CO_2e emissions - across all production stages. Information stored for the material genealogy allows mapping geometrical areas of a given production stage to any other production stage. This information can, for example, map a defect area of a hot rolled coil to any other production stage. This enables quality related evaluations covering the whole production chain.

The material genealogy is implemented as a graph consisting of nodes and directed edges. Each node describes a material at a specific production stage. Each edge describes a material transformation with respect to geometric, physical and chemical characteristics, i.e. a performed production step. A user interface is available to visualize the material specific genealogy graph and to obtain process related information for a material’s production history.

For determination of the PCFs (as “Quality Indicators”) along the production route from cradle to gate, master data with GHG emission factors for different material, electrical energy, steam and process gas consumptions as well as related process input data and calculation rules have to be configured within dedicated process specification dialogues (cf. Fig. 2). Thus, different PCFs can be configured,

- per production step and over all performed steps,
- with distinction between gross and net emissions, i.e. with and without by-side products and scrap cuts,
- as well as total emissions containing additionally all idle times and preparations of production campaigns as lump-sum contributions from the related production area.

This is supported by a hierarchical definition of GHG emission factors (cf. Fig. 3). Emissions related to raw material additions (scope 3), electrical energy (scope 2) and chemical energy (e.g. natural gas, scope 1) inputs for heating, as well as metallurgical reactions (like oxide reductions or decarburization, scope 1) can be calculated on the level of :

- individual production steps,

- individual production lines (aggregates)
- or areas of production lines.

The respective emission factors can be distinguished for different steel grades and products.

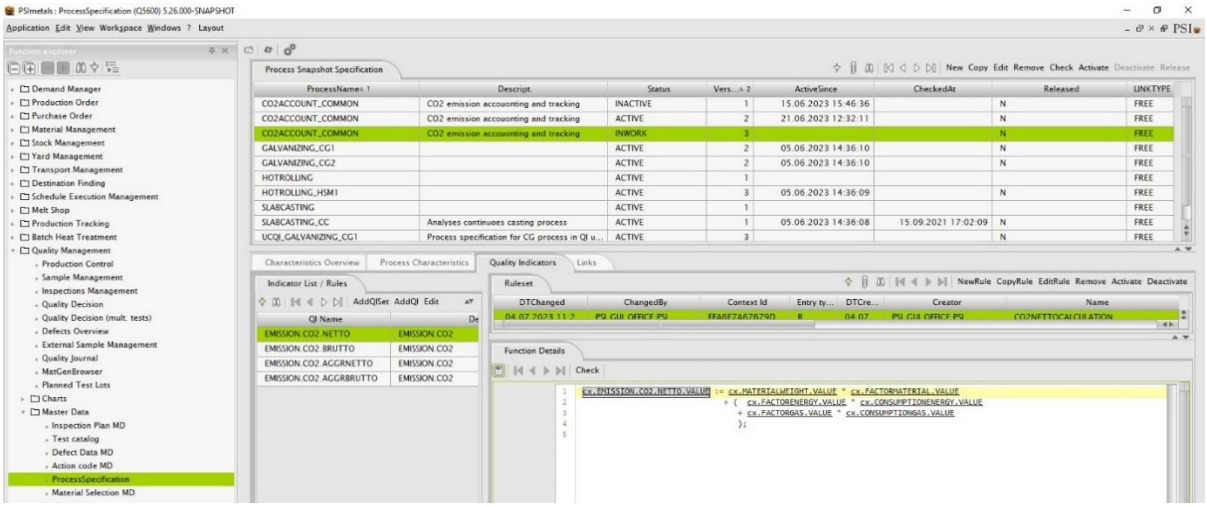

Fig. 2 - PSImetals Dialogue for Quality Process Snapshot definition with specification of PCF output variable

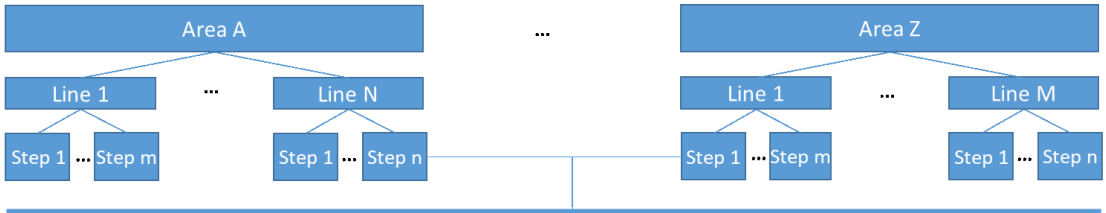

Table GHG Emission Factors

Column Name	Data Type	Constraints	Description
FACTORID	VARCHAR2(32)	PK	Unique Id of factors
AREA	VARCHAR2(30)	FK	Production area defined in own table
LINE	VARCHAR2(10)	FK	Production line defined in own table
STEP	VARCHAR2(10)	FK	Production step defined in own table
GRADE	VARCHAR2(10)		Steel grade according to own table, wildcard using * possible
PRODUCT	VARCHAR2(10)		Product according to own table, wildcard using * are possible
EMISSIONTYPE	VARCHAR2(20)		Specific type of emissions, e.g. CO2, CH4, N2O, ...
FACTORNAME	VARCHAR2(100)		Name of the conversion factor, e.g. MATERIAL, GAS, ELECTRICITY, ...
FACTORVALUE	NUMBER		CO2 emission in kg for 1 unit related to factor
UOM	VARCHAR2(30)		Unit of measurement related to factor: pc, kg, m³, kWh, ...

Fig. 3 - Hierarchically defined GHG Emission Factors

The scope 3 emissions of raw material additions have to be determined from their master data, i.e. their specific PCF provided by the supplier. GHG emission factors for the calculation of scope 2 emissions given in kg CO_2e / kWh electricity have to consider the mix of primary energy used to generate the consumed electrical energy. Scope 1 emissions related to fossil fuel (e.g. natural gas) or carbon carrier (e.g. injection coal) combustions are calculated from the associated emission factors, e.g. given in kg CO_2e / m³ gas or kg CO_2e / kg coal, respectively. The other group of scope 1 emissions in steel production result from metallurgical reactions which are mainly a reduction of oxides by carbon or carbon monoxide and decarburization of liquid steel, e.g. by BOF, RH, VD/VOD or AOD treatments. The reduction reactions can be treated like chemical heating with GHG emission factors given in kg CO_2e / m³ gas, kg CO_2e / kg coal or kg CO_2e / kg coke. For the decarburization reactions, a mass balance of carbon before and after decarburization results in the amount of emitted CO_2. If this is not available for individual heats, the calculation can use appropriate scope 1 emission factors per kg of decarburized input material based on evaluations of historic heat data. The higher levels in the accounting hierarchy consider emissions that are not taken into account in the lower levels. For example, emissions from idle times or preparations of next production campaigns, which cannot be assigned to a single product after

its treatment in a specific production step, must be configured on the area or line level as a kind of lump-sum contribution per kg of produced steel. Thus, the total PCF results from the sum of all levels of the hierarchy. Area factors are processed only once per product, line factors once per line cycle, each with the first related production step. The PCF calculations are triggered by production reports after finishing of each production step. With splitting of a material, the CO_2e emissions of the mother piece are distributed to the children pieces, according to their weights. On the other hand, joining of materials results in an aggregation of the involved CO_2e emissions to the new piece.

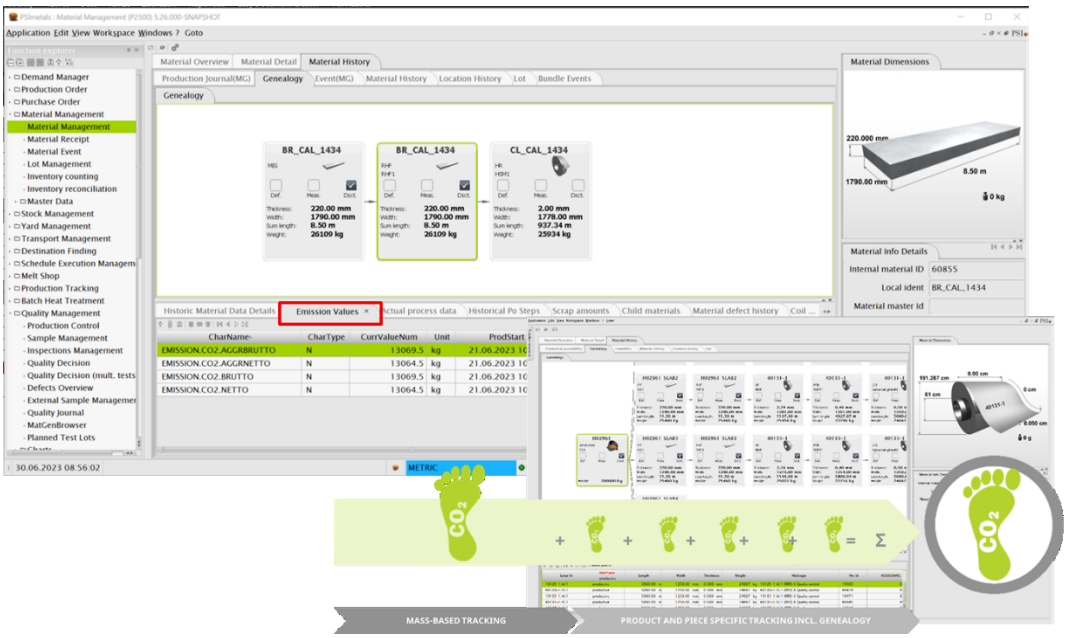

Fig. 4 - Visualization of PCF tracking in PSImetals material genealogy

There are valuable databases with material and energy consumptions, as well as related GHG emissions for steel production, e.g. from worldsteel life cycle inventory (LCI) study [8], which can be used as a basis for the configuration of the PCF tracking rules and master data.

A visualization of the calculated and tracked PCFs along the whole production chain, as well as a detailed tab displaying the CO_2e emissions from the individual process steps and their aggregated values for the respective product piece, can be seen in Fig. 4. Additionally, an embedded business intelligence (EBI) dashboard enables the evaluation of all information about PCFs of products, product groups, certain lines and areas including their evolution over the past weeks, months and years. This allows the detailed tracking of the improvements regarding decarbonization of steel production.

IMPLEMENTATION OF PCF TRACKING AT TATA STEEL

Tata Steel operates a fully integrated steel plant in IJmuiden, with a steelmaking capacity of 7 million tons per annum. The site produces high-quality flat steel products for global markets, including engineering, automotive, packaging and construction.

The production process begins with iron ore, which is processed in the sinter and pellet plants. Coal is converted into coke in the coke oven plants. These materials, along with pulverized coal are used in two blast furnaces to produce pig iron. The pig iron is transferred to the basic oxygen steel plant, where its carbon content is reduced via oxidation. Scrap metal is added to regulate the temperature. By adding alloying elements a large variety of liquid steel qualities are prepared. The resulting liquid steel is cast by continuous casting and processed into a strip product at the hot strip mill. Alternatively, liquid steel may be processed into strip at the direct sheet plant. Depending on customer requirements, the steel may undergo additional processing in the cold strip mill, galvanizing, painting, lamination or tin-plating lines.

Tata Steel in IJmuiden is currently one of the most CO_2-efficient integrated steel plants in the world. In the Heracless green steel plan, a new configuration is foreseen to produce liquid steel via a direct reduced iron plant, operating on natural gas and/or hydrogen and an electrical arc furnace to further reduce the CO_2-emissions. The first step includes decommissioning of one coke oven plant and one blast furnace, targeting a 40% CO_2 reduction in 2030 [9].

Reaching net-zero emissions will require continuous improvements throughout the entire production process. In this context, comprehensive CO_2 footprint tracking will support both transparent reporting and ongoing performance optimization.

Mass Balance Based PCF Tracking

In a first step, Tata Steel in IJmuiden provided GHG emission factors as average values per kg of produced steel at the different production areas, lines or steps. These values could be determined on the basis of statistical evaluations of the annual tonnages of steel produced in the different production lines and areas and the associated greenhouse gas emissions corresponding to the respective material and energy consumptions. The PCF tracking based on these material factors for specific GHG emission has been implemented in the first version for the solid production after end of casting. The PCF of the slabs from their iron and steelmaking as well as casting processes is initialized from the configured GHG emission factors of these production areas. The subsequent production steps of the slabs and coils are evaluated according to the respective material input, output and scrapped weights to calculate the net and gross CO_2e emissions of these steps as well as the aggregated emissions of the tracked product from all steps so far. Fig. 5 shows a screenshot from the productive MES at Tata Steel with results of such a PCF calculation for a strip product.

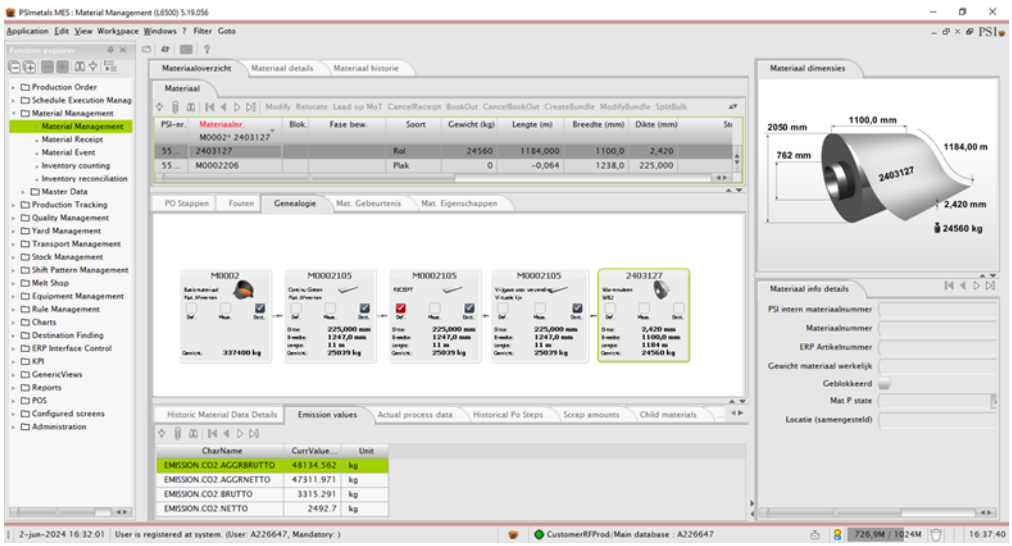

Fig. 5 – Example of CO_2 emission calculations for a strip product

Dedicated Consumptions Based PCF Tracking

The next expansion stage of PCF Tracking at Tata Steel includes the detailed accounting of emissions in the liquid steelmaking area utilizing scope 1 and scope 3 CO_2e emission factors per kg input material (hot metal, DRI, scrap, alloys, carbon carriers, slag formers, etc.). Thus, the emissions from iron making area are considered as initial upstream scope 3 emission values. For the subsequent production chain the CO_2e emissions are tracked per piece of material on the levels of

1. production steps in a line, based on the individual consumptions of electricity, gas and input materials during the respective steps, where these consumption data are available
2. production lines in an area (Steelmaking, Slab Finishing, Hot Rolling, Cold Rolling, etc.), where emission

relevant consumptions measured for the respective lines cannot be assigned to a specific production step with some material

3. production areas, where emission relevant consumptions measured for the respective areas cannot be assigned to a specific production line or step with some material.

Calculations on the levels of production lines or areas take into account lump-sum emissions, e.g. from idle and production preparation times. They are allocated to single pieces of material via appropriate material GHG cost factors based on mass balances evaluated with historic production and lump-sum consumption data, as described above for the PCF tracking implemented with the first version.

The next version also includes additional quality indicators related to the different emission contributions from scope 1, scope 2 and scope 3, respectively, in order to track them separately. Moreover, the emission class of a tracked piece of material according to the Low Emission Steel Standard (LESS) [6] is determined as a further quality indicator via implementation of the corresponding calculation rules. It is defined by 5 thresholds for the emissions accumulated until hot rolling which depend on grade (group of quality steels or structural and reinforcing steels) and the quota of scrap in relation to total input of pig iron, DRI, HBI and scrap. Additional adjustment rules consider compensations of higher emissions necessarily caused by certain grades and processes compared to the reference cases defining the thresholds (e.g. due to higher consumptions of alloys and slag formers or higher yield losses of the hot rolled products).

CONCLUSIONS

A manufacturing execution system with quality management based on process snapshots along all production steps provides an ideal framework for product carbon footprint (PCF) tracking. PSImetals has implemented this type of PCF approach using hierarchically defined GHG emission factors on levels of production area, production line and production step. Thus, CO_2e emissions can be calculated and tracked in real time on piece and product level along the complete chain of production steps and the results are stored on the related material genealogy nodes. This also includes lump-sum contributions to GHG emission from idle or preparation times of production lines that can be configured by appropriate area emission factors given in kg CO_2e / kg steel. At Tata Steel in IJmuiden a first version of PCF tracking has been installed based on average GHG emissions per kg of steel produced in the different production areas, lines or steps. In a next expansion stage the dedicated material and energy consumptions per production step shall be evaluated to determine the carbon footprint of an individual piece of product according to its actual production processes.

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MULTI-AGENT-BASED APPROACH FOR DECREASING CARBON FOOTPRINT OF FUTURE INTEGRATED STEELWORKS: THE AGIFLEX OVERALL CONCEPT

Ismael Matino, Valentina Colla, Lorenzo Vannini – Scuola Superiore Sant'Anna, TeCIP, Italy
Henrik Saxén, Carl Haikarainen, Mikko Helle, Meng Li, Guanwei Zhou, Kati Kemppainen - Åbo Akademi University, Finland
Thorsten Hauck, Maximilian Bernds, Achille Fabien Nkwitchoua Djangang, Bernd Kleimt, Andreas Wolff, Hauke Bartusch, Vera Peiss - VDEh Betriebsforschungsinstitut, Germany
Peter van den Broeke, Jan van der Stel - Tata Steel Nederland, Netherland
Jonas Prudente, Heike Busch, Michael Hecht - Dillinger, Germany

Steel sector is facing a deep period of transformation for achieving decarbonization target set by the European Green Deal. In integrated steelworks, significant modifications are envisaged involving both production and gas and energy management. Therefore, current production and energy management schemes must be revised to enable gradual and sustainable integration of C-lean processes. The European project AgiFlex aims at developing cutting-edge multi-agent based tool to fill the lack of ICT tools addressing the mentioned challenges. The overall AgiFlex concept is presented in the contribution.

KEYWORDS: FUTURE INTEGRATED STEELWORKS – AGENT SYSTEM – CARBON FOOTPRINT

INTRODUCTION

The European Green Deal challenges the steel sector to implement breakthrough modifications to significantly decrease its carbon footprint, and European steel producers are planning consistent investments in this direction. Integrated steelworks are particularly affected as, besides production process changes, important modifications are envisaged also for gas and energy management. Injection of H_2-rich gases in blast furnaces, and replacement of blast furnace-basic oxygen furnace route with direct reduction-electric arc furnace route will significantly affect the site-wide gas supply. The replacement of fossil materials and energy sources implies challenges related to intermittent renewable energy and gases (e.g. green hydrogen) with consequent fluctuation in energy availability and prices. Therefore, current production and energy management schemes must be revised to enable gradual and sustainable integration of C-lean processes.

THE AGIFLEX PROJECT

The European project co-funded by the Horizon Europe programme and entitled "*Agent-based models minimizing carbon usage in flexible and efficient future integrated steelworks*" (AgiFlex, G.A. 101138813) develops a cutting-edge tool to fill the lack of ICT tools addressing the above-mentioned challenges. A multi-agent approach is applied for production and energy management, which is based on digital twins of production units and advanced optimized framework. Its aim is process monitoring and control and optimal process integration in terms of conditions, material and energetic resources along the whole production chain.

Slight insight on Multi-Agent Industrial Systems

As stated in [1], an agent is "*An entity which is placed in an environment and senses different parameters that are used to make a decision based on the goal of the entity. The entity performs the necessary action on the environment based on this decision*." Similarly, [2] highlights that "*there are several versions of the agent concept, but all agree that autonomy is the main characteristic*".

In industrial settings, production systems are typically composed of a sequence or network of interconnected processes. The process system can be considered a set of interconnected entities, called unities. Some unities are autonomous decision-making components with internal state, or active agents, and some are passive transformation units, or passive agents. Therefore, the industrial process system can be considered a Multi-Agent System (MAS) characterized by a set of interacting agents exhibiting the following key properties [3]:

autonomy, decentralization, cooperation, coordination, and self-organization, intelligence.

The Agiflex overall concept

AgiFlex aims at developing a holistic MAS-based tool for process and energy integration with the goal to find promising operation points and configurations of the steel plant with respect to efficient carbon use. In this approach, the flowsheet of the plant is not a priori fixed and the sustainability of the steel production chain can be optimized considering external and internal constraints. This will allow tackling the challenging problem of minimizing the environmental impact of steelmaking during the transition phase of this industrial sector to sustainable operation. Figure 1 provides as schematic overview of the AgiFlex concept.

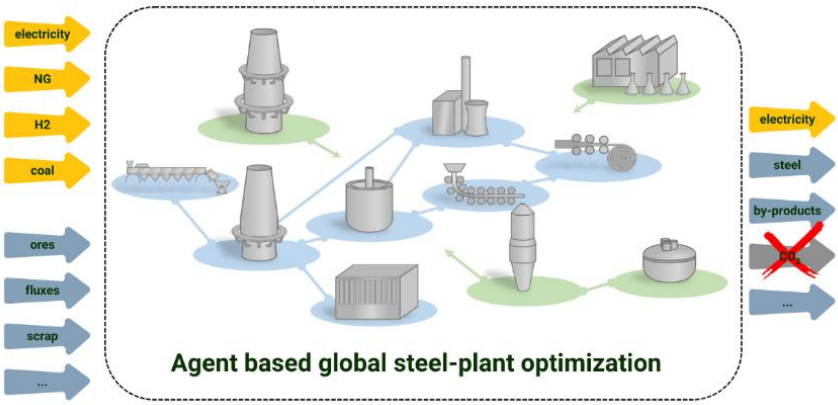

Fig.1 - Agent-based tool for assessment of CO_2 emission mitigation strategies in steel industry

An initial project phase aims at specifying the requirements of the agents, of the optimization framework, and in general of the whole system. Then, Digital Twins (DTs) are developed for steelmaking and ancillary units, gas production and conversion and external energy flows. DTs will constitute a repository of units that can be included or excluded in scenario analyses of future steel plants with the goal of minimizing the environmental impact. A validation and test phase will be carried out after the implementation of developed digital twins and optimization strategies in the agent framework. Finally, a demonstration phase at two industrial sites is foreseen for revealing completely new, promising low emission plant configurations and operation strategies, and the external conditions under which they are feasible. The analysis will also clarify the potential offered by flexible operation to mitigate environmental impact and improve economic benefits by demand site response.

ACKNOWLEDGEMENTS

Work described in the present contribution has been developed within the project entitled "*Agent-based models minimizing carbon usage in flexible and efficient future integrated steelworks*" (AgiFlex, G.A. 101138813). It has received funding from the Horizon Europe programme of the European Union, which is gratefully acknowledged. The sole responsibility for the issues treated in the present contribution lies with the authors; the Commission is not responsible for any use that may be made of the information contained therein

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Fast and robust order-based scheduling to solve the Mid-Term planning problem

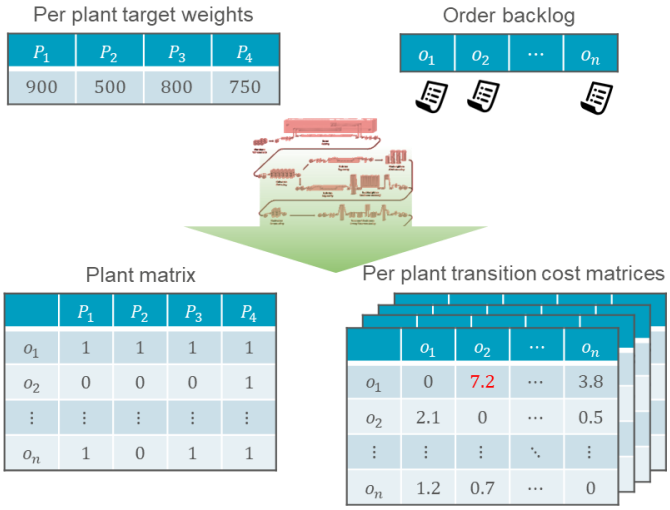
J. Brandenburger – VDEh-Betriebsforschungsinstitut, Germany

This paper presents a solution for the flat steel production mid-term planning problem focusing on the determination of best per-plant order sequences from a given set of orders (order backlog). The orders can be processed at multiple lines of a given production step and the solution should provide valid per-plant sequences considering any plant constraint on the one hand while minimizing the amount of required setup coils on the other hand. A mid-term solver has to select orders from the order backlog automatically, assign them to a certain plant and define valid per-plant production sequences. Furthermore, to be able to integrate as many different constraints as possible, a solver should be able to consider local (order-to-order) as well as global constraints (based on the full order sequence).
We present the DynReAct mid-term planning module exploiting Tabu-Search combined with a Traveling-Salesman Solver.

KEYWORDS: PRODUCTION PLANNING – SCHEDULING – FLAT STEEL – OPTIMIZATION – DIGITALIZATION

The DynReAct midterm planning is part of the hierarchical planning approach described in [1] which is implemented in the DynReAct open source production planning software [2]. The implemented mid-term planning component implements a hybrid approach combining a tabu search algorithm with a TSP solver and is based on the idea of finding the best order-to-plant assignments for each production step considering the constraints for each plant and the objectives for each step.

The input of the optimization problem for an exemplary production step with four alternative plants is shown in Fig. 1. These are the per-plant target weights to be produced, the orders available in the order backlog, a plant matrix defining if an order 0_i can be processed at a certain plant P_j and per-plant cost matrices defining virtual production cost of producing order 0_j after 0_i at a certain plant.



P_1	P_2	P_3	P_4
900	500	800	750

o_1	o_2	⋯	o_n

	P_1	P_2	P_3	P_4
o_1	1	1	1	1
o_2	0	0	0	1
⋮	⋮	⋮	⋮	⋮
o_n	1	0	1	1

	o_1	o_2	⋯	o_n
o_1	0	7.2	⋯	3.8
o_2	2.1	0	⋯	0.5
⋮	⋮	⋮	⋱	⋮
o_n	1.2	0.7	⋯	0

Fig.1 – Example inputs for mid-term planning module for a production step with 4 possible plants

To optimize order-to-plant assignments a tabu search approach was implemented where in each iteration the best candidate from a given neighborhood is selected according to a given target function (1). To solve the scheduling problem given in DynReAct the suitable Neighborhood was selected as allowed re-allocation of an order o to an alternative plant $pnew$, where $pnew$ can be also the non-assignment being that an order is not produced for the current solution.

This neighborhood contains new order-to-plant assignments and for each of them the TSP solver can calculate the hamiltonian path, being the cheapest path according to the order-to-order transition costs, which produces all assigned orders.

In detail, DynReAct applies the following weighted target function T_s with

$$T_s := \sum_{p \in Plants} N_{lots}(p) + \alpha_w \cdot \left(\frac{|W_{target}(p) - \sum_o w_o|}{W_{target}(p)} \right)^2 + \alpha_L \sum_o LC(o,p) + \alpha_C \sum_{L \in Lots(p)} TCosts(L) + \alpha_P \cdot NCaps(p) + \alpha_D \cdot NGroup(p) \quad (1)$$

and

$\alpha_w, \alpha_L, \alpha_C, \alpha_P, \alpha_D$	Weight factors for different aspects
$N_{lots}(p)$	Number of lots for plant p
$W_{target}(p)$	Target weight for plant p
w_o	Order weight of order o
$LC(o,p)$	Logistic costs of order o to plant p $:= \min_{c \in o} LCC(PP_c,\ p)$
$LCC(PP_c,\ p)$	Logistic costs of current plant PP_c of a coil to destination plant p
$TCosts(L)$	Total cost of Hamiltonian path
$NCaps(p)$	Monotonic behaviour (Number of critical width sequences)
$NGroup(p)$	Number of critical product group changes (< 50 t)

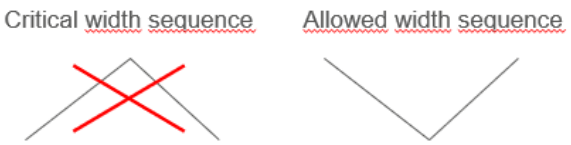


***Fig.2** – Critical width sequence*

In this context a critical width sequence is a small-large-small width change as shown in Fig.2 and a critical product group change refers to a minimum size of an aggregated product group weight to be processed before another product group can be started (e.g. 50t).

Once such a path contains a cost arc above a certain threshold it means that the orders cannot be processed in sequence and a new lot is created, being a sequence of orders that can be produced without interruption. In the target function as well the number of lots as the costs of the full path are considered. Furthermore, to get out of local minima, the tabu search implementation applies a shuffling approach randomly re-allocating previously allocated orders to the “not-assigned”-plant.

The presented hybrid Tabu-Search approach has the advantage that it always provides a valid production schedule, which can be used in production or improved in further Tabu-Search iterations making it a fast and robust solution for order-based scheduling in industrial scheduling problems.

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OPTICAL MEASUREMENT OF RAW MATERIAL PARTICLE SIZE

Christian Dengler, Mathis Kral and Georg Strüber – Paul Wurth (SMS), Luxemburg

The physical properties of raw material play an important role in the iron and steel making processes. Especially the grain size is important, e.g., for permeability control in the blast furnace or the densification of the sintering process. However, current grain size measurement methods are often irregular, labor-intensive, and rely heavily on manual effort, limiting the ability to achieve real-time process optimization, e.g., with the help of level 2 automation systems like process optimization systems like BFXpert.

This paper presents the development and testing of smart sensors designed to automate raw material grain size measurement using existing optical sensor technologies. Our approach aims to overcome the limitations of traditional methods by providing continuous, automated, and accurate grain size data, with open interfaces and edge computing, suited for the integration in automation systems. This enables more precise process control and improved product quality.

This paper focusses on the evaluation of machine learning segmentation algorithms to use with a generic 2D industrial camera within the dedicated image processing pipeline. Additionally, a complementary system using a high-resolution 3D laser line scanner is explored qualitatively to assess its potential for specialized diagnostic applications.

KEYWORDS: PARTICLE SIZE DISTRIBUTION, SMART SENSOR, PROCESS AUTOMATION, MACHINE VISION, CONVEYOR BELT MONITORING

INTRODUCTION

The efficiency, stability, and product quality of iron and steelmaking processes, such as the blast furnace and Direct Reduced Iron (DRI) plants, are intrinsically linked to the physical properties of their input raw materials. Among these properties, the Particle Size Distribution (PSD) is a critical parameter. It directly influences the permeability of the burden in the blast furnace shaft, the kinetics of chemical reactions, and the densification behavior during sintering. An inconsistent or out-of-specification PSD can lead to process instabilities, increased fuel consumption, and reduced output.

Traditionally, PSD is determined through manual sieve analysis. This method, while standardized, is labor-intensive, time-consuming, and performed on small, discrete samples. The resulting data is infrequent and may not be representative of the bulk material flow, creating a significant delay between measurement and potential process adjustments. This reactive approach rules out the possibility of using the PSD data as input for real-time, feed-forward process control systems such as BFXpert [1].

To overcome these limitations, automated, online measurement systems are required. Optical sensors present a promising approach for continuous, non-contact analysis of material on conveyor belts. While similar systems are commercially available, we are developing our own to ensure seamless integration with the BFXpert level 2 system, tailor measurements for the ironmaking and steelmaking industries, and leverage the latest developments in AI and computer vision. The primary contribution of this work is a quantitative analysis of recent zero-shot segmentation models to identify the most robust algorithm for real-world particle analysis in ironmaking. The segmentation algorithm plays a crucial role in the conversion of the 2D image to an estimation of the particle size distribution and chosing the best algorithm is essential for this task. The presented analysis is part of the thesis [2], which presents an even more detailed analysis of segmentation algorithms.

Furthermore, we explore a complementary approach using a high-resolution 3D laser line scanner. While not subjected to the same quantitative validation in this study, this technology is discussed qualitatively to highlight its potential for specialized applications where direct three-dimensional measurement offers unique advantages.

BACKGROUND AND RELATED WORK

The need for automated particle size analysis is recognized across many heavy industries, including mining, cement, and aggregates. Commercial systems for on-belt analysis predominantly use either camera-based (2D) or laser-based (3D) techniques.

Camera-based systems, often referred to as dynamic image analysis systems, capture images of material flow and apply software algorithms to determine particle characteristics. Products like the BeltMetrics (Motion Metrics) use high-speed cameras and sophisticated lighting to analyze particles, offering real-time data for process control [3]. These systems have proven effective for monitoring crusher performance and ensuring product consistency.

AI and machine learning are increasingly used to improve segmentation accuracy and reduce errors from human intervention. Publications using camera based systems in ironmaking include works on coke particles by Li et al. [4] and Sabharwal et al. [5], or works on sinter particles by Holliday et al [6]. The core challenge in these 2D image analyses lie in accurately segmenting touching or over-lapping particles and inferring a 3D property (volume) from a 2D projection.

Laser-based systems, which often use either laser diffraction or direct 3D scanning, provide an alternative that can overcome some limitations of 2D imaging. Laser line scanners, which operate on the principle of laser triangulation, project a laser line onto the material and capture its profile with a camera. By moving the material on a conveyor, a 3D height map of the surface is generated. Systems like the 3DPM from Optimation are designed for this purpose, claiming robustness as they do not require calibration against manual sieving and can directly detect areas of fines [7]. Publications using this method can be found from a research team at Luleå University of Technology that collaborated for the development op thementioned commercial system [8].

Beyond optical methods, acoustics also presents a viable, yet niche approach for estimating particle size distribution. An expired patent details a method where the sound of solids being poured into a vessel, such as a blast furnace, is recorded and analyzed to determine particle sizes [9]. However, we are not aware of any technical papers that have published results for this type of analysis in iron-making. For information on passive acoustic measurements of smaller particles, a comprehensive overview can be found in the literature review of Dr. Hamid Amrollahi's PhD thesis [10].

METHODOLOGY: AUTOMATED GRAIN SIZE MEASUREMENT SYSTEM

Experimental Camera Setup and Validation Method

Figure 1: Camera test stand setup [2](modified)

An simple experimental test rig, shown in Figure 1, was constructed to perform the measurements. The setup consists of a piece of conveyor belt and an adjustable mounting frame for the industrial camera. The sensor provides 9.1 megapixel images at 12 frames per second and a GeniCAM interface. The sensor was mounted directly above the center of the belt. We use a CUDA enabled Jetson Orin computer for the inference of machine learning models.

Several raw materials used in the iron and steel industry were tested, namely iron ore, pellets, sinter and coke.

The general pipeline for estimation the PSD is as follows:

1. Calibration and pre-processing: a one-time calibration procedure is performed using a calibration particles to determine the pixel-to-millimeter conversion factor.
2. Particle detection and segmentation: at the core of the image processing lies the detection (where are particles and of which material type) and the segmentation of the particles (what are the boundaries for that particle). Both tasks are performed using state of the art machine learning algorithms. This step is the main topic for this publication.
3. Particle volume estimation: to infer a 3D volume from a 2D projection, another data-based approach was developed. A digital library of 3D particles of each material type was created. The digital library contains the volume and a 2D projections of each particle in the library. In operation, a regression model based on features (area and shape descriptors) of the measured 2D projection of a particle segmented from the camera image are used to estimate the volume of the particle.
4. Mass Calculation: With the volume of each particle estimated and its material type known, the mass is calculated by assuming a standard bulk density for that material. The cumulative mass distribution provides the final PSD.

Our detection model is based on an existing detection model, fine-tuned on an in-house dataset of the different materials. This model is trained specifically to detect non-obstucted particles only, as detecting and segmenting partially obstructed particles would lead to a bias in the detected particle size distribution.
For the segmentation of the particles, we use pre-trained models, namely SAM [11], FastSAM [12], MobileSAM [13] , SAM2 and SAM2.1 [14]. Some of these models also come in multiple sizes, e.g., for the SAM2.1 model, there is a tiny, small, base and large model available. Since we also compare the model performance for different amounts of pixels, we compare the accuracy of 24 variations of those models against labeled images. The evaluation of the segmentation quality of those models is the main study provided in this paper.

The main metric we use for the segmentation quality is the Jaccard index, also known as intersection over union. This metric evaluates to 1 if the segmentation is a perfect fit with the label, and 0 if there is no overlap of the segmentation with the label. Segmented labels for the different materials are shown in Figure 2. Only non-obstructed particles are labeled.

In a production enironment, the camera images might not always be as clear as for our test stand. To account for this in our model selection, we also analyse how the segmentation quality degrades with degradation in image quality. We apply noise, blur and change of brightness to the image and observer the model performance for each change.

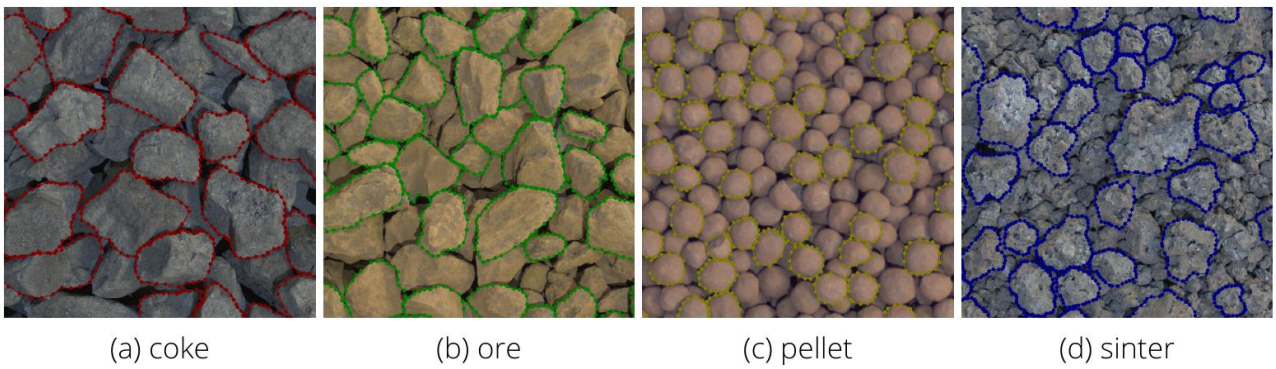

Figure 2: Segmentation labels for different materials [2]

The Laser Line Scanner

Figure 3: Laser scanner setup (Lab and on-site)

In our discussion later on, we later compare the camera qualitatively against two distinct sensor systems, shown in Figure 3. These systems utilize laser line scanners to generate a 3D height map of materials on a conveyor belt. Our test systems consist of:

- A laboratory setup featuring a small-scale conveyor belt.
- An industrial-grade production system designed for an iron-making plant, complete with a sensor unit, protective housing, and an electrical cabinet.

We were able to gains experience with the laser line scanners both in laboratory as well as in a production environment in cooperation with Rogesa.

RESULTS AND DISCUSSION

First, we analyse the segmentation quality of the different machine learning models on images captured by the camera system on the test stand. The segmentation quality, evaluated as the Jaccard index, is given per model and per material type in Figure 4. We see that the segmentation quality varies significantly based on three main factors: material properties, model architecture, and image size.

Influence of material properties:

The physical characteristics of each material directly impact segmentation performance.

- **Coke and Iron Ore**: These materials are easier to segment due to the clearly defined borders between particles.
- **Iron Pellets**: The segmentation quality, measured by the Jaccard index, is slightly lower for iron pellets. This may be due to the ratio of particle size to the overall image size.
- **Sinter**: This material proves the most challenging. Its ambiguous particle boundaries hinder the models' ability to create accurate masks.

Model performance and limitations:

The choice of model also plays a crucial role, with FastSAM models performing particularly poorly for two main reasons:

1. **Low-quality segmentation**: The intrinsic quality of the masks generated by FastSAM is inferior to other models (See Figure 5).
2. **Architectural flaw**: FastSAM does not correctly take the detections into account, but is selecting the particles to segment on its own. Instead of generating a new mask from a prompt, it simply selects one from a set of pre-calculated segments. This design leads to a high number of "misses," where the model fails to return a segmentation for the particle that is labeled.

The critical role of image size

Our analysis shows that image size has a greater influence on segmentation quality than the specific model or its size. The effect is most pronounced in larger models like SAM2.1-l, which struggle significantly with smaller images.
This performance gap is likely due to the model's internal architecture (its ViT image decoder), which in larger models is optimized for high-resolution images and struggles to adapt to smaller ones. The larger decoders in the large model variants appear optimized for high-resolution images, while the smaller decoders in the tiny variants demonstrate more flexibility with smaller images. This inability of the SAM2.1-l model to handle smaller resolutions is also evident in Figure 5.

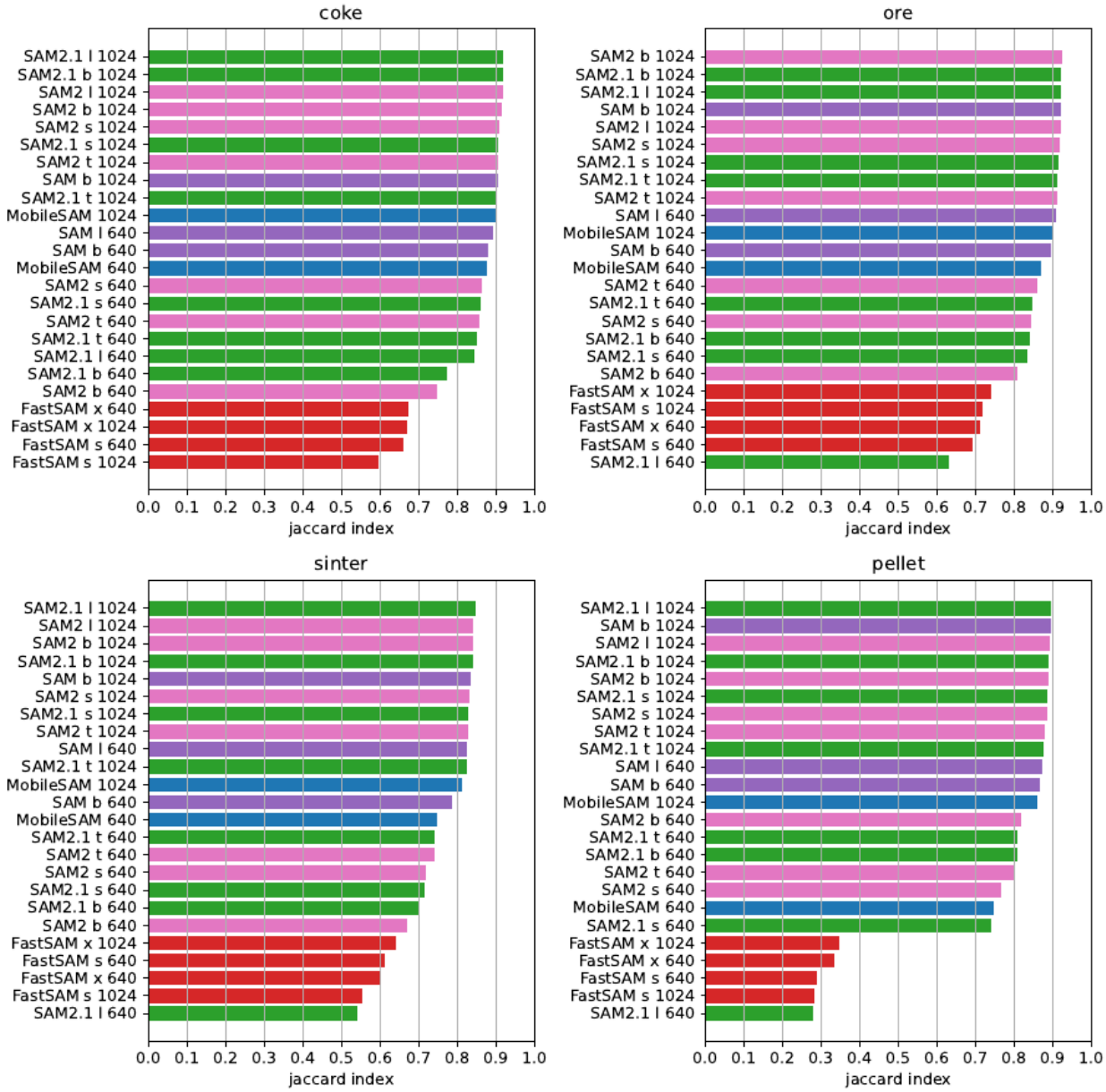

Figure 4: Segmentation quality per model per material [2]

Robustness against imperfect images
Next, we analyse the impact of artificial image noise, blur and brightness changes. The results show that material type and input image size remain the most significant factors influencing performance, consistent with the findings for unmodified images.

Impact of different transformations:

- Noise and Blur: The models are most sensitive to noise and blur. The impact varies significantly by material:
    - Coke and Iron Ore: These materials are highly robust, showing only a minor decrease in segmentation quality even with medium-to-strong transformations.
    - Sinter and Iron Pellets: These materials are much more sensitive. The complex texture of sinter and the particle size of the pellets cause a sharp drop in performance as noise or blur increases.
- Brightness: All models proved to be highly robust to changes in brightness. Increasing the brightness had almost no negative effect on segmentation quality. However, a significant *decrease* in brightness did degrade performance, an effect most pronounced on the already dark-textured coke and sinter materials.

Across all transformations, a consistent pattern emerged: models that perform well on clean images generally perform well on manipulated images. While all models can handle small amounts of image manipulation with little quality loss, the best overall performance is typically achieved by the same models that excelled on the original images.

There are, however, exceptions under heavy manipulation. For instance, while the SAM2.1-t model with a 1024px image size is superior on clean images, the smaller SAM2.1-s model (640px) can match or even outperform it when subjected to large amounts of noise or blur.

An visual example for the degradation of the segmentation quality is given in Figure 6 for sinter particles.

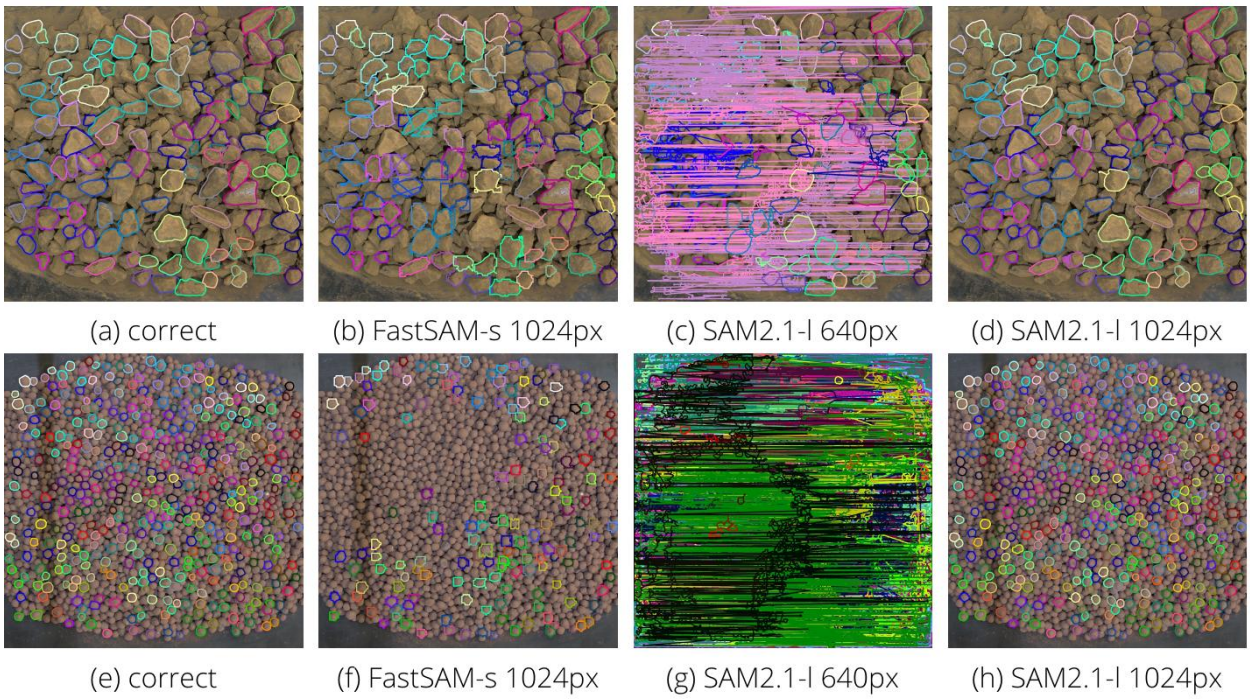

Figure 5: Qualitative segmentation results for selected models [2]

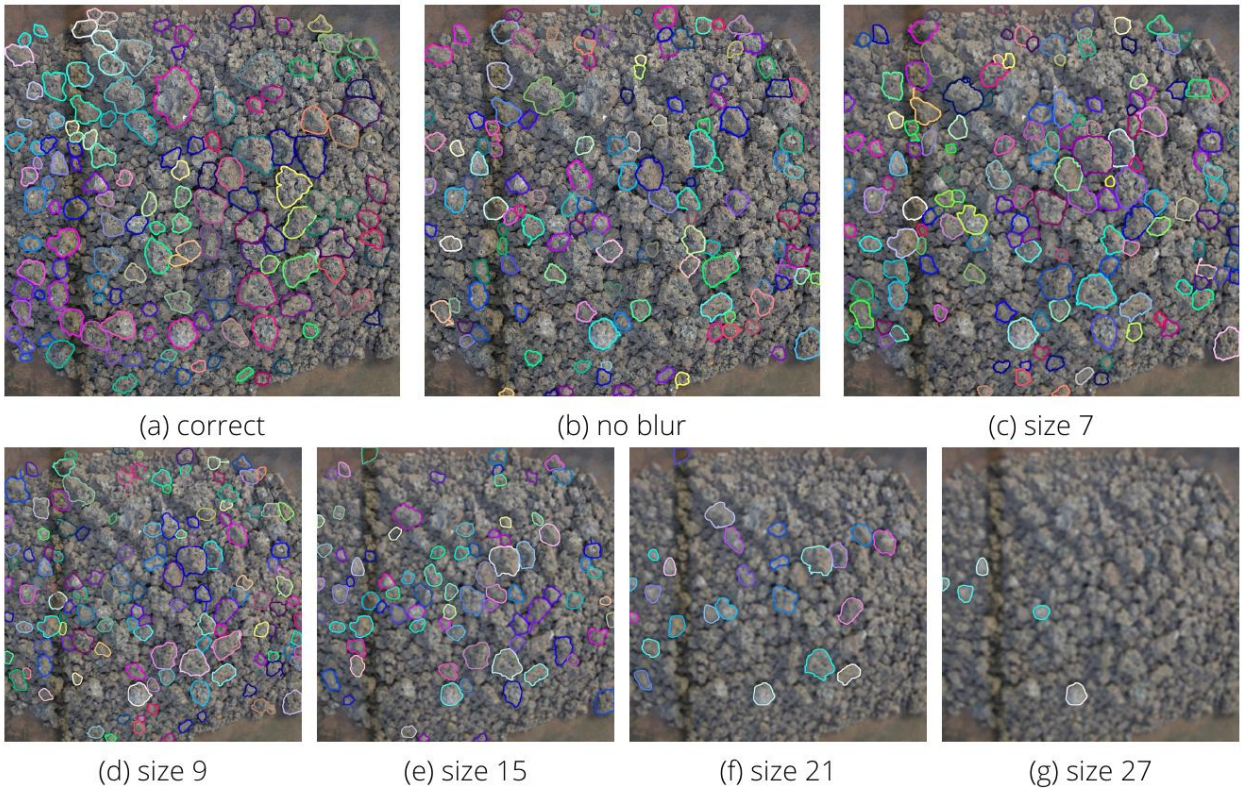

Figure 6: Qualitative degradation of segmentation quality under blur [2]

Discussion and System Comparison

The results confirm that a camera system using machine learning can accurately segment common ironmaking particles. This segmentation is the most critical step for calculating the Particle Size Distribution (PSD). Beyond the PSD, the system also provides data on particle shape—information not available from traditional sieve analysis. Furthermore, the model can identify and verify the different materials in the furnace feed mix.

In contrast, the laser scanner has several limitations. Its triangulation method creates blind spots behind large particles, hindering accurate 3D reconstruction. It also builds a height map from individual line scans, a process that requires a perfectly stable conveyor belt speed to avoid errors and makes it unusable away from a conveyor. Finally, the lack of color information makes material classification difficult.

Based on our experience, the laser scanner is best suited for monitoring fine particles or conveyor belt health, where it can detect even tiny scratches. For analyzing larger particles like coke or pellets, the 2D camera with machine learning is the more suitable approach. It is cost-effective, versatile, and accurate enough to track process trends and guide operational changes.

An ideal integrated system could, therefore, use the camera for routine process control and the laser scanner for periodic, in-depth diagnostics or quality audits.

CONCLUSION

This paper presented the development of an automated system for measuring the particle size distribution of raw materials on a conveyor belt. A camera-based system was developed and the segmentation quality of available models quantitatively compared. The approach demonstrates a high degree of accuracy and performance suitable for real-time process control.

In addition, a complementary system using a high-resolution 3D laser line scanner introduced for a

comparison and both approaches discussed.
Based on these findings, we recommend the camera-based approach as a practical, validated solution for general-purpose PSD monitoring in an industrial setting. For applications that demand the highest precision or true 3D surface information, e.g., for the detection of fines or monitoring of the health of the conveyor belt, the laser line scanner is a powerful complementary tool.
The adoption of such automated optical systems can lead to improved process stability, reduced operational costs, and enhanced product quality in the iron and steel industry.

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Optimized availability of a mechanical drive train through a holistic predictive maintenance approach

Veikko Äikäs – SEW-EURODRIVE GmbH & Co KG – Germany
Viktor Kubernat – SEW-EURODRIVE CZ s.r.o. – Czech Republik
Sami Kuokkanen – SEW Industrial Gears Oy – Finland

Condition monitoring-based predictive maintenance is often viewed as an add-on for ordered drive train solutions. This viewpoint can lead to lowering a drive train's availability and increasing the total cost of ownership. To truly maximize a drive train's availability and to reduce the total cost of ownership, the decisions made throughout the entire drive train's lifecycle must support this goal.

Optimizing a drive train's availability and total cost of ownership begins with the end user's project specification phase and continues until the drive package is decommissioned. This holistic approach applies to both mechanical and electrical drive technology solutions.

This white paper presents a holistic approach to optimize a mechanical drive train's availability and total cost of ownership. Market experiences are presented in the form of challenges. Decisions at important project gates for condition monitoring-based predictive maintenance solutions are discussed and presented for hot long rolling mill gear units.

This paper provides valuable insights for decision-makers and offers practical guidelines for engineers to optimize a drive train's availability and total cost of ownership. By adopting a proactive and holistic approach, organizations can significantly improve the reliability and longevity of their mechanical drive systems, ultimately leading to increased productivity, reduced downtime and reduced total cost of ownership.

KEYWORDS: PREDICTIVE MAINTENANCE – CONDITION MONITORING – MECHANICAL DRIVE TECHNOLOGY – INDUSTRIAL GEAR UNIT – HOLISTIC APPROACH – HOT LONG ROLLING

INTRODUCTION:

Objective of this white paper

In the first part, this white paper aims to describe the actual challenges faced when targeting optimum results in condition monitoring for predictive maintenance. The focus is on a mechanical drive train's optimization, specifically on an industrial gear unit. Later, this white paper aims to introduce improvements to the specified challenges. The answers aim to optimize a drive train's availability and to reduce the total cost of ownership.

What is included in this white paper?

The paper discusses challenges and improvements at important project gates. These important project gates include an end user's machine specification, an OEM's (Original Equipment Manufacturer) machine specification, an OEM's component specification to a sub-supplier, a sub-supplier's component specification to an OEM, and an OEM's supplier assessment and purchase decision. Each of these project gate decisions play a role in determining how a high degree of machine availability and low total cost of ownership can be achieved.

What is excluded from this white paper?

This paper does not focus on

1. efficient or effective general maintenance techniques for industrial gear units
2. different available condition monitoring sensors and data processing solutions
3. exact lifetime determination of each component in an industrial gear unit

4. different machine learning, artificial intelligence algorithms, digital twin and statistical model capabilities for the optimization of predictive maintenance results
5. couplings, joint shafts and base frames as part of the mechanical drive train package
6. electrical drive train components
7. avoiding failures during maintenance
8. different maintenance KPIs

PERCEPTION OF CHALLENGES FACING CONDITION MONITORING FOR PREDICTIVE MAINTENANCE

General

In general, increased global competition, limited project budgets and reduced project execution times can be seen as major challenges for the implementation of condition monitoring systems. Additionally, information exchange and the lack of condition monitoring specifications on the part of the end user limit the systems' results.

Increased global competition and limited project budgets

Increased global competition, over-capacity and a low demand for new machines all reduce available project budgets. This subsequently leads to cost pressure on mechanical drive train solutions, which reduces machine availability and increases the total cost of ownership. These challenges include the following:

A. In most projects, the end user is not permitted to influence the machine builder's decision regarding the supplier of the mechanical drive train. Through specific formulations of the machine specification, the end user is excluded from the decision-making process. This reduces and simplifies the end user's work, but at the same time gives the machine builder the full freedom to decide the component supplier.
B. Component suppliers and machine builders are forced to reduce safety margins in the selection and design process. This pressure is basically to be seen positively as it also leads to solution innovations. However, at the same time, it also leads to smaller component sizing, reduced safety and a decreased lifetime.
C. Falling solution prices associated with the CAPEX (capital expenditure) phase lead to an increased push to generate revenue via the service business. Using this approach, end users initially receive an optimized CAPEX solution, but at the same time the risk of paying remarkably more for the service activities or production loss through the drive train's lifetime is increased.

Reduced project run-through times

The market requires faster project execution times from the investment decision to the start of production. This time pressure leads to the following challenges:

D. The turn-key solution from the machine builder is an attractive solution. This reduces the iterative loops in the project work.
E. The standard solutions used earlier are copy-pasted to the new customer with minimum adaptations required. This leads to a situation where new solutions struggle to become part of the scope of delivery.

On the other hand, there is enough time to clarify details while in parallel waiting for the investment decision. This time is normally not used as work on detail clarification, as it is not seen as a must do.

Information exchange in the global supply chain

Global competition and supply chains pose a challenge for information exchange. Previously, the drive train solutions were implemented with known regional partners. Now, the component suppliers are coming from different countries or even globally. This leads to a point where a supplier solution and quality assessment are guided via specifications. As is the case with general information exchange, even the best specification can only include part of the features inside a component or part of a machine, such as a drive train. Many decisions made by the supplier remain unreachable for the end user's or machine builder's specification.

As a result of a commercial assessment, new unknown component suppliers may be preferred to remain within the project budget. This is a challenge for the OEM concerning the supplier solution and quality assessment.

Very often the original thoughts behind a supplier / machine-specification are not remembered and important details may not be checked in the supplier's solution and quality assessment.

Regarding industrial gear units, for example, the normally specified requirements include mechanical service factors, bearing lifetime and gearing safety. These performance indicators are influenced by several sub-factors, which can be freely selected by the supplier to some extent. These include, for instance, oil purity factors and modification factors for bearing lifetime determination. Such details are not specified by the end user's or OEM's specification, and the objectivity of the assessment is influenced.

A further example is maintainability. Details such as split housing and contactless sealing are known to be essential for easier maintenance. These are often missing from the specification. Figure 1 illustrates the missing information in the industrial gear unit specification.

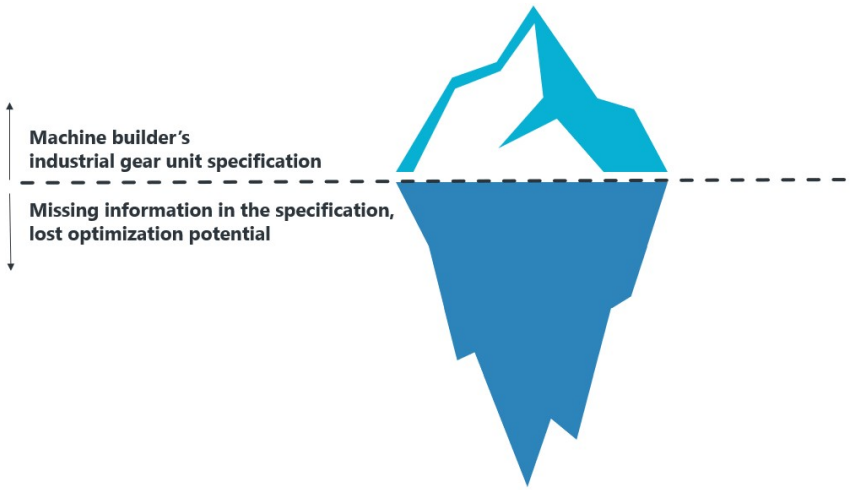

Fig. 1. Challenge related to the industrial gear unit's specification.

Missing condition monitoring specification
The end user's specifications appear to place little to no emphasis on condition monitoring solutions or the verification of their results. This leads to the fact that end users do not receive a well-thought-out condition monitoring solution.

IMPORTANT PHASES IN AN INDUSTRIAL GEAR UNIT'S LIFE CYCLE FOR PREDICTIVE MAINTENANCE

General
We focus on the following parts of the industrial gear unit's life cycle: The end-user's machine specification, the OEM's machine specification, the OEM's component specification to the sub-supplier, the sub-supplier's component specification to the OEM and the OEM's sub-supplier assessment and purchase decision. Figure 2 illustrates the main steps in the industrial gear unit's specification and verification workflow.

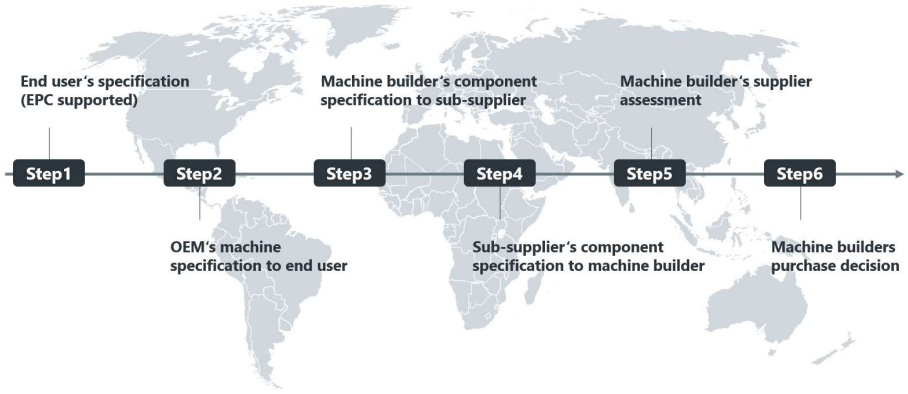

Fig. 2. Different steps in the industrial gear unit's specification and verification workflow

End user's machine specification

The end user's target is usually to define the performance parameters that the machine needs to be able to fulfill. EPCs (Engineering, Procurement and Construction) may have been supporting the end users in this specification work. These required parameters include, for example:

1. Production output in a defined time unit
2. Materials that are to be produced
3. Standards and regulations that need to be fulfilled
4. Desired start time of production
5. Available infrastructure
6. Available manpower / desired automation level

This specification seldomly has an influence on a sub-supplier's component selection, even though the individual components can have a significant impact on the machine's total cost of ownership. It is common for machine downtime in steel production to cost tens of thousands of euros per hour.

OEM's machine specification to the end user

An OEM's machine specification aims to define the performance parameters that their machine can guarantee for the end user. These are basically answers to the above-mentioned points regarding the end user's specification. The specification may also include general information about commonly used sub-supplier brands or solutions.

OEM's component specification to the sub-supplier

An OEM's component specification is a compromise between the end customer's wishes and the OEM's standard approach. The influence of the end customer's specification could reach this level, but seldomly does. The specification normally includes the following:

1. General information about the machine and the project
2. Atmospheric information about the installation location, such as temperature, humidity, corrosiveness
3. Used motors, couplings, brakes, joint shafts and their influence through external forces on the gear unit
4. Performance parameters such as turning speeds and torques
5. Required service factor, bearing lifetime, minimum safety
6. Specified oil
7. Available cooling media
8. Project documentation

Sub-supplier's component specification to the OEM

A sub-supplier's component specification to the OEM is normally a part of the budgetary or binding offer. These offers normally include:

1. Project name

2. Input data such as speed, power and torque
3. Achieved service factors and bearing lifetimes
4. Specified oil
5. Selected cooling type

OEM's supplier assessment and purchase decision
An OEM's technical supplier assessment normally includes the following steps: fulfillment of the specified requirement, the OEM's previous experiences, the sub-supplier's references and, if required, a visit to the sub-supplier.

The purchase decision is normally made by the purchasing team. The supplier is selected from the suppliers that are approved by the engineering team. The company that has the best price and delivery performance for the specific project normally has the best chance of receiving the order.

It is important to note that anything that is not specified as required will not contribute to the decision. For instance, if easy maintainability was not clearly specified, it will not be included. It will be seen an additional cost for the industrial gear unit supplier and will not be beneficial for the OEM, even though the end user may appreciate it.

HOLISTIC CONDITION MONITORING-BASED PREDICTIVE MAINTENANCE APPROACH AND IMPROVEMENT POSSIBILITIES FOR A HOT LONG ROLLING MILL GEAR UNIT

Holistic condition monitoring-based predictive maintenance approach
In the holistic condition monitoring-based predictive maintenance approach, the important project gate specifications and decisions are used as a basis for optimized availability and reduced life-cycle costs. Possibilities for improvement are presented below. These improvement aspects should flow through the above-mentioned specification work from the end user to the component supplier. Figure 3 highlights the areas of improvement presented in this white paper.

Fig. 3. Components of a holistic condition monitoring-based predictive maintenance approach

Pre-project to determine critical components, their lifetime and maintainability
It is possible to design an industrial gear unit that has an extremely long service life or excellent maintainability. However, this is often not done due to time and budgetary limitations. A solution for this challenge could be a pre-project approach. In such a pre-project, the end user's lifetime expectations can be discussed at a component level and summarized as part of the end-user's specification. Subsequently, these results can be used as a basis for generating a maintenance plan.

For example, to achieve a theoretical lifetime of 30 years, the end user's specification could include the

following requirements - either during the offer stage or, at the latest, during the detailed engineering phase of the order:

A. Please include a condition monitoring system in the scope of supply. Its capabilities, as defined in the machine builder's specification, should be described according to the following categories:
    a. Which components of an industrial gear unit can be monitored regarding their condition?
        i. Subsequently, how are these components monitored?
        ii. What are the additional maintenance activities, when using the condition monitoring solution?
    b. Which components of an industrial gear unit cannot be monitored regarding their condition?
        i. Which design/engineering/assembly activities contribute to achieving the expected lifetime?
        ii. Which maintenance activities need to be taken care of by the end user to achieve the desired theoretical lifetime?
    c. Please specify each component criticality (series / parallel) for machine operation.
    d. Please define the expected failure modes during the expected lifetime with pictures.
B. Please specify the parameter limits for an oil analysis to ascertain when the oil must be changed
C. Please specify the warning and emergency vibration limit levels for the warning system

Smart, digital, time adapting, maintenance guidelines for an industrial gear unit

An OEM's maintenance manuals or guidelines are currently presented in a very static format. These consist of task lists concerning daily, weekly, monthly or yearly tasks and their respective descriptions. These task lists do not take into consideration how long the unit has been in operation. A unit that has been in operation for 3 months is considered the same as a unit that has been in operation for 15 years.

A smart, digital time adapting maintenance guideline could be generated to overcome this challenge. This digital maintenance guideline can include traditional elements such as a maintenance logbook as a basis to determine the required maintenance. At the same time, the solution can include the latest information from the used condition monitoring sensors and data analyzer. With an interactive touch, this digital solution can improve the maintenance accuracy for the end user. Examples:

1. Oil change only when the oil reaches the limit values specified by the supplier in an oil test.
2. Bearing change only when the vibration levels increase to warning or emergency levels.
3. The complete component is changed when the unit reaches the theoretical end of its lifetime. In other words, a point in which the defined lifetime is reached with the corresponding probability.

Oil sampling and oil lubrication system

The first indicator for the onset of wear is the oil. Oil should be considered as a component of an industrial gear unit and therefore needs to be monitored carefully and changed when needed. A premature oil change costs money, while a late oil change reduces the machine's lifetime.

The process of regularly sampling the oil from individual industrial gear unit oil sumps or central oil lubrication systems is highly important. Sampling points must be in positions that allow accurate analysis to obtain a true representation of the oil that is lubricating the gear unit's components.

Determining the time of an oil change is not easy. There are simple cases in which the oil is like new, or there are cases in which the oil clearly exhibits metal particles, or the deficiency of additives. Then there are the more difficult cases. To achieve a certain lifetime, industrial gear unit manufacturers presume a certain cleanliness of the oil. The results of the oil sample and the target lifetime information can be used to decide whether the oil needs to be changed. In the best case, the limit values for the oil test sample are listed in a specification document that is provided with the operation manual of the industrial gear unit. The end user is then able to concentrate on maintenance with the predefined information.

A condition monitoring solution for a lubrication system is generally based on pressure and flow sensors. These two inform the user if there is a malfunction in the main or side pipeline. The malfunction could be, for

example, local clogging of a nozzle.

Firstly, it is beneficial to inform the user of the minimum pressure and flow values that guarantee the intended lubrication of components. This would reduce the unneeded maintenance work. Secondly, these pressure lubrication points can be difficult to reach if the design has not taken into consideration the maintainability. The end user's specification can provide the requirements regarding this maintainability.

Verification of vibration measurement results

The most used condition monitoring method for predictive maintenance is the vibration measurement. The vibration measurement mainly provides information about the geared parts and bearings. The primary target of the measurements is to ensure that the correct maintenance procedure takes place at the correct time. However, it is also worth noting that the vibration measurement can reduce the need for spare units and spare parts in stock. The amount of capital tied up in an end user's inventory is already determined in these specification phases.

Vibration measurement is always advisable as a supplement to other diagnostic methods such as endoscopy and oil analysis. Unfortunately, the components are sometimes hard to reach regarding endoscopy. A well-prepared specification can maximize the number of components accessible for endoscopy, for example, through hatches or dedicated threaded inspection ports. Table 1 presents an overview of different condition monitoring measurement methods and emphasizes the importance of using a mix of methods for measurement and verification.

Tab. 1 – Condition monitoring measurement methods for an industrial gear unit

GEARBOX	Diagnostic method and its suitability								
Type of defect	Torque (current) meassurement	Oil flow measurement	Oil pressure meassurement	Vibration measurement	Wear particles detection	Speed monitoring	Endoscope - visual check	Temperature measurement	Motion camera
Gearing defect	●			●●	●●●		●●●	●	●●
Bearing defect	●	●		●●●	●●●		●●	●●●	●●
Unbalance				●●●					●●●
Bad lubrication		●●●	●●●	●●	●●●		●	●●●	
Surface corrosion					●●		●●●		
Misalignment				●●●				●	●●●
Mechanical looseness				●●●					●●●
Wrong base frame				●●					●●●
Exceeding the operating speed	●●			●●●		●●●		●●	●
Exceeding operating load	●●●			●●●				●	●●

Gear housing type and seals

All too often, discussions concerning the gear unit's housing revolve around the materials used. One of the less discussed topics for the housing is its maintainability. The largest industrial gear units come with split housing, while the housings of the smaller series are normally of a monobloc type. The difference between a split and monobloc housing can make a big difference to maintainability on-site.

Small but important components in the industrial gear unit are the seals. The lifetime of shaft seal rings is influenced by numerous aspects such as environmental influence, compatibility with the used oil or grease, and the installation of the seal. Contactless seals offer maintenance freedom, however, their suitability needs to be checked regarding the operational parameters. Whichever seal solution is recommended by the supplier, it needs to be aligned to the end user's requirements. For instance, an end user's specification could include maintenance freedom, and a simple replacement without removing couplings or joint shafts.

Torque measurement at frequency converter

When assessing the remaining lifetime of an industrial gear unit, one of the first questions will be about the

load applied to the gear unit, input shaft and output shaft. In general, it is very rare for end users to have retained loading data that covers the full operational lifetime. Besides difficulties assessing the remaining lifetime, the missing loading data also poses a further challenge. In the event of failure, it is more difficult to make design improvements.

To calculate the theoretical remaining lifetime of a gear unit, a requirement for such data and systems can be an integral part of the end user's specification. The torque information from the frequency converter is accurate enough for most of the applications to assess the remaining lifetime of individual components. Ideally, in applications in which there is a frequent variation in torque level, the gear unit is equipped with torque measurement at both the input and output.

Repair and replacement plan
At some point, the industrial gear unit may require a repair. Ultimately, it will reach the end of its lifetime. In both cases, the end user is faced with the question: "How do I solve this problem?".

In the end user's specification, the end user can require repair, and replacement plans from the OEM, machine and component supplier. In addition to the technical plan, these plans could also include approximate repair / replacement time plans. This would help the end user to be better prepared for events that could happen sooner or later. As a practical example, this information can be used to determine whether a spare unit is needed in stock. The required plan may already be part of the offer or order scope as a non-binding rather than a binding plan.

Integration into a higher automation system
The integration of component level condition monitoring into a higher-level automation system requires certain input information. This information can also be included in the end user's specification to help maximize the effectiveness of ERP (Enterprise Resource Planning) systems by enabling the use of specific predictive maintenance modules.

SUMMARY
This paper discusses the importance of the holistic approach to condition monitoring-based predictive maintenance. Firstly, the market challenges are addressed. In general, the increased global competition, limited project budgets and reduced project execution times can be seen as major challenges for implementation of condition monitoring systems. Additionally, information exchange and missing condition monitoring specifications from the end user's side limit the systems' results.

Secondly, the important steps in the industrial gear unit life cycle are addressed. The focus is placed on the end user's machine specification, the OEM's machine specification to the end user, the OEM's component specification to the sub-supplier, the sub-supplier's component specification to the OEM and the OEM's supplier assessment and purchase decision.

Thirdly, the holistic approach is used to determine improvements for an industrial gear unit in an example application of a hot long rolling mill. The suggested improvements include the following:

1. pre-project approach for determination of critical components, their lifetime and maintainability
2. a smart digital and time adapting maintenance guideline
3. an improvement of the oil sampling and oil lubrication system
4. verification of vibration measurement results
5. a gear unit's housing and seals
6. torque measurement at the frequency converter
7. repair and replacement plan
8. integration into a higher automation system

The improvements presented can be used by end-users and machine builders alike to improve the solutions, thereby targeting maximum machine availability and minimizing total cost of ownership.

HYMAS: A HYBRID MULTI-AGENT FRAMEWORK FOR AUTONOMOUS STEEL PRODUCTION PLANNING

Anton Ivanov, Ralf Lenz, Heiko Wolf– PSI Software SE

Steel is a cornerstone of global infrastructure but its production faces inherent complexity due to high energy consumption, strict quality demands, and sophisticated production process. While traditional planning methods rely on rigid, centralized frameworks, they struggle to adapt to disruptions like equipment failures or material defects, leading to inefficiencies and financial losses. These complexities require autonomous, intelligent solutions that rapidly generate and propose optimized schedules, enabling swift, data-driven rescheduling in response to disruptions. To address this, we present HyMAS, a Hybrid Multi-Agent System, which enables dynamic, resilient decision-making in steel manufacturing. HyMAS employs a hierarchical network of autonomous agents: resource agents govern separate lines, process agents manage entire production stages, and process chain agents coordinate sequential operations. This modular structure allows localized adjustments to production plans without requiring full-scale re-planning, significantly reducing decision time and increasing flexibility. Integrated with Industry 4.0 frameworks, the system interfaces with Manufacturing Execution Systems, leverages digital twins to simulate disruption impacts, and applies machine learning to predict material quality and process mining to monitor performance. In a case study involving a cold rolling mill, three annealing lines, and intermediate storage, HyMAS achieved an 18% efficiency gain and an 8% improvement in on-time delivery. These results demonstrate the system's ability to improve operational performance while maintaining high levels of adaptability. By leveraging autonomous, intelligent agents, HyMAS rapidly generates and proposes optimized schedules, empowering manufacturers to mitigate financial risks, reduce decision time, and enhance operational agility. Additionally, planning adjustments can now be implemented much more swiftly than before, ensuring a more resilient and responsive production environment. By gradually integrating autonomous, intelligent rescheduling into production planning, HyMAS unlocks the potential of real-time data to systematically enhance efficiency, responsiveness, and operational resilience.

KEYWORDS: SCHEDULING – PLANNING – MULTI-AGENT SYSTEM – DIGITAL TWIN – HYMAS

INTRODUCTION: HEADING

Steel production underpins global infrastructure, yet its manufacturing processes remain among the most complex and disruption-prone in the industry. Production is highly energy-intensive — a single continuous annealing line can consume up to 400 MWh per day — and must meet stringent quality standards while coordinating tightly sequenced operations under strict delivery deadlines. Traditional planning in steel plants relies on centrally generated, deterministic schedules. These static plans are slow to adapt when confronted with unplanned events such as equipment breakdowns, material defects, or urgent order changes, often triggering manual, time-consuming re-planning. The result is efficiency loss, missed delivery targets, and increased operational risk.

The increasing complexity of supply chains and the volatility of customer demand underscore the need for planning systems that are adaptive, autonomous, and resilient. Industry 4.0 principles — digitalization, decentralized decision-making, and real-time analytics — create an opportunity to replace static scheduling with systems capable of self-adjustment. Multi-agent systems (MAS), digital twins, and AI-driven analytics have emerged as promising enablers, allowing distributed agents to negotiate, cooperate, and respond locally to disturbances without triggering full-scale re-planning.

Previous research has demonstrated that MAS architectures can enhance flexibility, fault tolerance, and responsiveness in industrial scheduling [1]. Building on these foundations, this work presents HyMAS — a Hybrid Multi-Agent System that integrates the adaptability of autonomous agents with the precision of mathematical optimization models. HyMAS autonomously generates and adjusts production schedules in near real time, guided by a digital twin that simulates the impact of disruptions and by optimization models that balance objectives such as tardiness minimization and reduction of dummy coils ("stringers").

Our industrial focus is the cold-rolling and continuous annealing stage, where efficient scheduling is crucial both for meeting downstream delivery commitments and for avoiding waste from unnecessary stringer use. The HyMAS framework employs a hierarchical agent model — resource, process, and process-chain agents — to localize decision-making while maintaining global coherence. This is coupled with a Parallel Heterogeneous Annealing Lines Scheduling (PHALS) that explicitly models multi-mode processing options and operational constraints [2].

The remainder of this paper first defines the steel production scheduling problem and outlines the specific operational challenges encountered in cold-rolling and annealing stages. It then describes the HyMAS architecture and its integration with a digital twin, followed by an explanation of the PHALS optimization model and how it is embedded within the agent framework. Next, the paper presents the simulation-based validation and case-study results. Finally, it concludes with a discussion of the contributions to resilient autonomous scheduling and perspectives for future research.

PROBLEM STATEMENT: COLD-ROLLING AND ANNEALING SCHEDULING CHALLENGES

The production setting considered here consists of a cold rolling mill followed by several continuous annealing lines — three in the case study. After cold rolling, coils must be annealed to achieve the specified material properties, using either batch furnaces or continuous annealing lines (CALs). In continuous annealing, coils are welded end-to-end into a single strip that passes through a high-temperature furnace at a constant speed. This arrangement enables high throughput but also imposes strict sequencing constraints: consecutive coils must be compatible in physical properties and process requirements. Large differences in annealing temperature profiles, thickness, or width can prevent direct welding.

When incompatibilities occur, a dummy coil — known as a stringer — must be inserted between the coils to preserve continuous furnace operation. Stringers are not part of any order and their use is undesirable: they consume material and energy, reduce throughput, and require extra post-processing for removal.

Scheduling cold-rolled coils onto multiple CALs is therefore a multi-criteria optimization problem. Each coil has a due date and may offer alternative processing modes — for example, different annealing temperature–speed combinations that meet the required metallurgical properties. The scheduler must determine:

- **Line assignment** – which CAL will process each coil.
- **Sequencing** – the order of coils on each line.
- **Mode selection** – which processing mode to apply when alternatives are available.

These decisions must satisfy key objectives and constraints:

- **Efficiency** – maximize continuous operation and minimize stringer insertions.
- **Tardiness minimization** – meet delivery deadlines or reduce lateness.
- **Flexibility** – accommodate real-time changes such as breakdowns or urgent orders.

The problem is NP-hard, combining features of parallel machine scheduling, sequence-dependent setups (welding compatibility), and due-date constraints [2]. Its difficulty is compounded by the frequency of disruptions in steel plants: a CAL may fail, a strip may break, or a high-priority order may arrive unexpectedly. Such events can instantly render a static plan infeasible. For example, if one line fails, its coils must be reassigned to the remaining lines; if an urgent order appears, it must be inserted without disproportionately

delaying others.

Addressing this challenge requires dynamic rescheduling — the ability to revise the plan in real time, mitigating the impact of disruptions while preserving overall efficiency and delivery performance. The combination of combinatorial complexity and operational uncertainty motivates a solution that blends optimization for high-quality plans with an agent-based architecture for decentralized, rapid responsiveness.

SYSTEM ARCHITECTURE: HYBRID MULTI-AGENT SYSTEM (HYMAS)

The HyMAS architecture is a hierarchical and modular multi-agent system designed to support real-time, resilient scheduling in steel production. Its structure mirrors the physical and organizational structure of the production process, with decision-making distributed across several layers. The system is connected to the plant's digital infrastructure through an open API and interacts directly with the Manufacturing Execution System (MES), a plant digital twin, and external services such as optimization algorithms, predictive analytics, and process-mining tools.

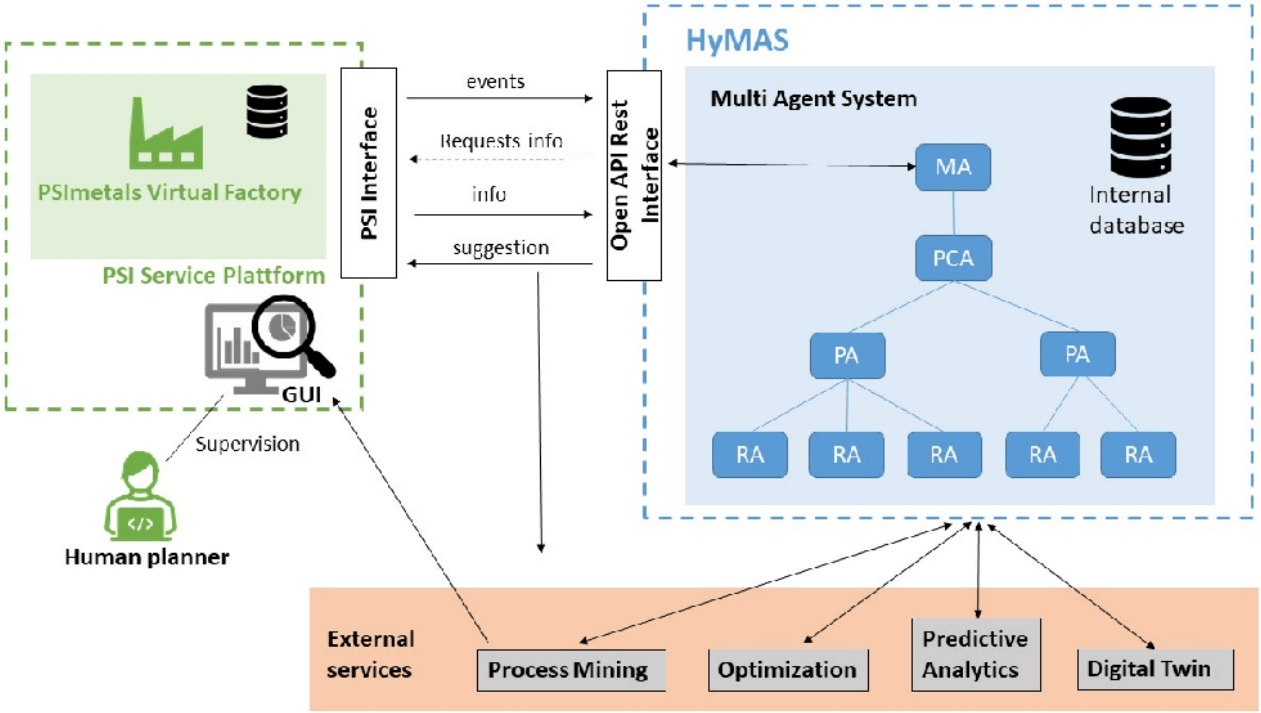

Fig. 1 - HyMAS Architecture

At its core, HyMAS is composed of the following agent types:

- **Resource Agents (RA)**: Represent individual machines or production lines, such as a specific annealing line or the rolling mill. Each RA is responsible for local scheduling and execution, proposing job sequences for its resource and monitoring progress. RAs can negotiate task handovers or sequencing changes through their supervising agents when disruptions occur.
- **Process Agents (PA)**: Manage entire production stages composed of multiple resources. For example, one PA may coordinate all annealing lines, while another manages the rolling stage. PAs aggregate constraints and schedules from their subordinate RAs, ensuring that all resources within the stage operate in synchrony and that workload is balanced.
- **Process Chain Agent (PCA)**: Coordinates the full production sequence across all stages. The PCA maintains a global view of throughput, inventory, and delivery performance, ensuring capacity alignment between upstream and downstream processes and adjusting plans to resolve bottlenecks.
- **Master Agent (MA) – optional**: Functions as a supervisory or integration layer, particularly for

external communications. In the present implementation, the PCA fulfills this role, so a separate MA is not explicitly required.

The “hybrid” nature of HyMAS refers to its combination of autonomous agent-based control with embedded optimization models. Each agent is equipped with decision-making modules that can range from lightweight heuristics to advanced mathematical programming solvers. This design enables a two-tier decision process. First, when a disruption occurs, agents respond within seconds using simple heuristics to maintain continuous operation — for instance, rerouting coils to other lines if one goes offline. Second, more computationally intensive optimization algorithms run in the background to refine the schedule over a longer horizon. When these algorithms produce an improved plan, the update is propagated across the system without interrupting ongoing execution.

Integration with the MES ensures that all schedules are based on up-to-date production data and can be directly executed on the shop floor. The digital twin enables the simulation of “what-if” scenarios, allowing major plan changes to be tested virtually before implementation. Predictive analytics modules, based on machine-learning models, forecast issues such as potential quality deviations or equipment failures, enabling proactive schedule adjustments. Process-mining tools continuously analyze operational data to identify inefficiencies and recurring bottlenecks; the resulting insights are used to adapt both heuristic rules and optimization models.

Through this architecture, HyMAS combines the flexibility and resilience of decentralized decision-making with the precision of advanced optimization, delivering rapid, well-coordinated responses to disruptions while continually improving plan quality.

SCHEDULING MODEL: PHALS OPTIMIZATION FOR ANNEALING LINES

To complement the agent-based architecture, an advanced scheduling optimization model was developed for the annealing stage of production. This model, referred to as PHALS (Parallel Heterogeneous Annealing Lines Scheduling) [2], captures the core decision problem of assigning and sequencing cold-rolled coils on multiple annealing lines. Its objectives are twofold: to maximize throughput by reducing both stringer usage and idle time, and to meet delivery due dates.

The problem considers a set of steel coils $\{1,2,\dots,N\}$ that have completed cold rolling and await annealing on M parallel lines with potentially different technical specifications. Each coil i has a due date D_i and may have one or more admissible processing modes, representing alternative annealing “recipes” (temperature–speed profiles) capable of meeting metallurgical requirements. Processing a coil in a given mode on a specific line determines both its processing time and its compatibility with other coils. When two consecutive coils are incompatible — for example, due to large width differences or conflicting temperature requirements — a dummy coil (stringer) must be inserted. Stringers are undesirable, as they consume time, energy, and material without contributing to production. The scheduling task therefore involves deciding for each coil: which line to assign it to, in which position to place it within that line’s sequence, and which processing mode to use. The goal is to minimize stringer insertions and tardiness while respecting processing-mode feasibility and line capacities.

The problem can be formulated as a mixed-integer linear program (MILP) [2]. However, solving it exactly becomes computationally infeasible for realistically sized instances due to the combinatorial growth of sequencing possibilities. To address this, a tailored two-phase heuristic approach was designed, combining the speed of graph-based algorithms with the precision of MILP applied to small subproblems:

- **Phase 1 – Constructive Sequencing via Shortest Path**: The sequencing problem for each line is formulated as a shortest-path search on a directed acyclic graph (DAG), where nodes represent the “last processed coil” state and arcs correspond to scheduling a specific next coil. Arc costs reflect penalties for stringers or lateness. A shortest-path algorithm is applied to generate a near-optimal sequence for each line in a simplified setting, minimizing local penalties while ensuring all coils are assigned. This step produces an initial feasible schedule quickly by greedily reducing local costs.
- **Phase 2 – Improvement via Fix-and-Optimize:** Starting from the initial solution, the schedule is refined through iterative fix-and-optimize decomposition. In each iteration, a subset of decision

variables — such as the sequence on one line or a group of coil assignments — is re-optimized using an exact MILP solver, while the rest of the schedule remains fixed. Examples include re-sequencing a single line's coils or swapping assignments between lines when this reduces stringers or delays. This systematic exploration of subproblems incrementally improves global schedule quality.

Experimental results with industry-inspired datasets show that this approach consistently outperforms a state-of-the-art commercial MILP solver in producing high-quality solutions within short computation times. In particular, PHALS achieves fewer stringers and lower tardiness under the same time limits, making it well-suited for the fast decision cycles required in HyMAS.

Within the HyMAS framework, PHALS is primarily applied at the Process Agent (PA) and Process Chain Agent (PCA) levels. The PA for the annealing stage receives coil orders, due dates, and current line status from the MES via the HyMAS interface and uses PHALS to generate an optimized annealing plan. This plan is communicated to the relevant Resource Agents (RAs) as a target sequence. RAs execute the plan locally, applying small heuristic adjustments if minor disturbances occur — for example, swapping two compatible coils when one is delayed in arrival. The PA can also re-run PHALS periodically in a rolling-horizon manner or immediately after a major disruption. The PCA ensures that the annealing schedule remains consistent with upstream and downstream operations, for instance by slowing the rolling stage when annealing becomes a bottleneck or by triggering re-optimization with updated priorities.

In summary, PHALS provides the analytical engine within HyMAS for optimizing the annealing stage. By explicitly modeling multi-mode, parallel-machine scheduling with domain-specific objectives, it enables the agent system to produce high-quality, disruption-resilient production schedules that are both computationally efficient and operationally realistic.

INTEGRATION AND APPICATION

The HyMAS framework was implemented as a prototype and evaluated through simulation in a realistic steel production environment. This required both software and process integration between the academic prototype and industrial systems.

The core HyMAS agents were developed using the JIAC multi-agent framework — a Java-based agent middleware from TU Berlin — and extended with custom HyMAS optimization modules. On the industrial side, the plant's Manufacturing Execution System (MES) provided the simulation environment and a graphical user interface for monitoring and interaction. Communication between HyMAS and the MES was handled via a RESTful API. This interface allowed the agents to subscribe to production events, request information, and transmit schedule updates or recommendations. The two-way communication ensured that the simulation state and agent decisions remained synchronized at all times.

For evaluation, a case study was configured using realistic data from a cold rolling and annealing operation. The simulated plant setup included one cold rolling mill producing coils for an intermediate buffer, a finite-capacity storage area where coils awaited annealing, and three parallel continuous annealing lines. The lines differed in process speeds and coil-size capabilities, reflecting the heterogeneous nature of the real facility. Approximately 200 coil orders of varying grades, dimensions, and due dates were scheduled over a multi-day planning horizon. Some orders required strict prioritization due to tight deadlines, while others had more flexible delivery windows.

The digital twin was loaded with this configuration, and realistic operational variability was introduced to test system adaptability. This included stochastic annealing line stoppages, random minor delays, one simulated rush order arriving mid-horizon, and occasional quality deviations requiring reallocation or reprocessing of coils.

During the simulation, HyMAS was responsible for monitoring events, adapting schedules, and proposing

updated plans. Human planners could observe these proposals in the GUI, review their associated key performance indicators (KPIs), and decide whether to accept them.

To assess performance, HyMAS was benchmarked against a conventional static planning approach. The baseline plan was generated in advance for all orders, without dynamic rescheduling. When disruptions occurred, the baseline approach simply paused and resumed execution as closely as possible to the predefined sequence, without re-optimization. In contrast, HyMAS continuously updated schedules in response to events, allowing for dynamic reallocation and sequencing adjustments.

Three KPIs were used to compare performance:

- **Operational efficiency**: productive time of annealing lines and the number of stringers used.
- **On-time delivery rate**: percentage of coils delivered by their due dates.
- **Rescheduling responsiveness**: time required to produce a meaningful updated schedule after a disruption.

This setup provided a controlled yet realistic environment for validating HyMAS's ability to deliver more efficient, timely, and disruption-resilient scheduling compared to conventional static methods.

RESULTS AND DISCUSSION

The simulation experiments demonstrated clear performance benefits of the integrated HyMAS approach compared to a conventional static plan. Table 1 summarizes the results. The dynamic, agent-driven scheduling of HyMAS yielded notable gains in both operational efficiency and delivery timeliness.

HyMAS improved annealing line efficiency by approximately 18 %, increasing average utilization from 75 % under the static plan to 88–90 %. This improvement was largely driven by the system's ability to intelligently group compatible coils, thereby minimizing stringer insertions and reducing idle periods. The average number of stringers required per 100 coils fell from 5.2 to 1.1 — an almost fivefold reduction. By inserting stringers only when absolutely necessary, HyMAS not only improved throughput but also lowered material waste and energy consumption.

Tab. 1 - Performance of static planning vs. HyMAS approach

Performance Results		
Performance Indicators	**Conventional Static Plan**	**HyMAS**
Annealing Lines Efficiency	75%	88-90%
On-Time Delivery Rate	85%	92%
Average number of stringers per 100 coils	5.2	1.1
Average Responce Time to Disruption	~30 min	< 1 min

Delivery performance also improved substantially. With HyMAS, 92 % of orders were completed on or before their due dates, compared to 85 % for the static plan. The gain was a direct result of dynamic rescheduling: when disruptions threatened to delay specific orders, HyMAS agents reprioritized affected coils and adjusted sequences to preserve on-time performance wherever possible. In contrast, the static plan, once disrupted, often led to cascading delays that impacted multiple orders downstream.

Importantly, HyMAS had to balance two potentially competing objectives: maximizing efficiency and minimizing tardiness. While pushing for absolute efficiency might delay some urgent orders, and eliminating all tardiness could require suboptimal line utilization, the multi-objective optimization within HyMAS effectively managed

this trade-off.

From an industrial perspective, these improvements are significant. An 18 % increase in line efficiency translates into substantial annual savings through higher throughput and lower energy usage, while an 8 % increase in on-time delivery directly enhances customer satisfaction and supply chain reliability. The ability to generate a viable reschedule in less than one minute — compared to around 30 minutes for the static approach — reduces work-in-process accumulation and stabilizes operations, giving planners confidence that routine disturbances can be resolved autonomously.

Overall, the results demonstrate that HyMAS delivers resilience, responsiveness, and efficiency improvements that align with the Industry 4.0 vision of self-regulating, smart manufacturing systems. For complex production environments such as steel plants, this approach enables a transition from static, manually managed schedules to adaptive, autonomous planning.

CONCLUSION

This work presented a Hybrid Multi-Agent System (HyMAS) integrated with an advanced scheduling optimization model to address the complexity of steel production planning. The framework enables resilient and autonomous scheduling that adapts dynamically to disruptions while optimizing key operational objectives. HyMAS combines a distributed, hierarchical decision structure — with Resource, Process, and Process Chain Agents — and embedded optimization modules, achieving a balance between the agility of local decisions and the rigor of global optimization.

In a realistic case study involving a cold rolling mill and multiple continuous annealing lines, HyMAS achieved substantial performance gains: up to an 18 % increase in throughput and an 8 % improvement in on-time delivery compared with a conventional static planning approach. These gains were accompanied by significant reductions in stringer usage and scheduling response times, underscoring the system's ability to deliver both efficiency and reliability.

From an academic standpoint, the results illustrate how coupling multi-agent system architectures with operations research techniques can yield robust, scalable solutions for complex industrial scheduling problems. The hierarchical MAS structure provided modular, stage-level control, while the PHALS optimization model served as a computational engine capable of handling the combinatorial complexity of multi-mode, parallel-machine scheduling. The hybrid design leveraged the strengths of both approaches: the responsiveness and local autonomy of agents, and the optimality-seeking capabilities of mathematical programming. This synergy represents a promising pathway for future smart factory implementations.

For industrial practitioners, the findings demonstrate the potential for tangible gains in operational performance without requiring major infrastructure changes. By dynamically re-optimizing production plans in response to events, HyMAS reduces downtime, improves delivery performance, and minimizes waste from inefficient sequencing. Its deployment can be incremental: initially functioning as a decision-support tool that provides real-time, optimized scheduling proposals to human planners, and later evolving toward full autonomy as confidence in the system grows. In such a setup, planners shift their focus from routine rescheduling to managing exceptions and aligning operations with strategic objectives, thereby reducing scheduling workload and increasing overall system resilience.

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Artificial Intelligence-based decision support system for optimizing the ladle furnace process in the ALCHIMIA project

S. Dettori[1], L. Laid[1], A. Zaccara[1,4], V. Colla[1], I. Matino[1] L. Vannini[1], T.A. Branca[1], M. Vannucci[1], A. Siddique[1], F. Rossi*[2,3], M. Niero[2,3] –

[1]Sant'Anna School of Advanced Studies, TeCIP Institute, Italy, [2]Sant'Anna School of Advanced Studies, Sustainability and Climate Interdisciplinary Center, Italy, [3]Sant'Anna School of Advanced Studies, Institute of Management, SUM (Sustainability Management) Lab, Italy, [4]Università di Padova, Dipartimento di Ingegneria Industriale, Italy

This contribution presents a decision support system helping ladle furnace operators in the optimization of the process operation in terms of electricity consumption and additive materials. The decision support system includes tools developed through artificial intelligence-based techniques, such as genetic algorithms, which provide a framework for formulating and solving nonlinear constrained optimization problems, and neural networks-based models, which describe the complex chemical/physical reactions in the ladle furnace.

KEYWORDS: LADLE FURNACE – DECISION SUPPORT SYSTEM – ARTIFICIAL INTELLIGENCE – OPTIMIZATION – FERROALLOYS – GENETIC ALGORITHM - LCA

INTRODUCTION

The Ladle Furnace (LF) process is fundamental for refining steel before Continuous Casting (CC) and strongly affects some main mechanical features of the final semi-finished steel products. Ferroalloys, deoxidizers and slag formers are added to molten steel to adjust its chemical composition to meet the requirements of the specific steel quality to produce. During the process, the steel temperature is controlled within given boundaries through electricity-based heating systems, to reach the optimum temperature for CC without the risk of premature solidification, to reduce energy losses and avoiding quality problems (such as oxidation and wear of refractory materials). Many treatments, such as the addition of ferroalloys and the refinement of sulphur or oxygen content, are highly dependent on temperature. A stable temperature ensures solubility and reactivity of chemical elements. In addition, it is essential to control the microstructure and final mechanical properties, manage the time spent in the ladle and improve flexibility of production planning. Several aspects, such as the electricity consumption and amounts of materials to be added, can be optimized by formulating adequate control strategies, by considering the current state of the molten steel. Through a proper forecasting and optimization system, it is also possible to decrease the number of measurements of the steel chemical composition between additions, leading to an increase of productivity.

This work presents part of the activities carried out within the European project entitled "Data and decentralized Artificial intelligence for a competitive and green European metallurgy industry" (ALCHIMIA), which aims at optimizing the steel recipe in the EAF-based route in terms of energy, scrap mix and additive materials. In the project, three steelmaking plants are actively involved, by providing data, testing environments, knowledge and skills for designing digital tools aiming at improving the economic and environmental impact of the sector.

LF DECISION SUPPORT SYSTEM

During the project, a Decision Support System (DSS) is developed to provide LF operators with optimized

control solutions and a better insight in the environmental impact of the production cycle. The DSS includes a digital twin of the LF that leverages the paradigm of Federated Learning (FL) for training accurate Neural Network (NN)-based models and refining them through Continual Learning (CL) algorithms. CL consumes online local plant data for monitoring the effectiveness of the digital tools, and finally triggering a proper re-training of the models, once their accuracy falls below a certain threshold.

The digital twin exploits real-time data to forecast the final temperature and chemical composition of molten steel before CC through NN-based models [1] and is at the core of the optimization system that calculates the optimal LF operation. The optimization system is based on evolutionary algorithms to minimize a multi-objective function problem, comprising economic costs and environmental impacts, while satisfying production constraints, and a proper numerical description of chemical-physical processes involved.

Identifying the optimal combination of chemical additives, in terms of quantity and type, is a complex nonlinear problem, influenced by multiple factors such as temperature, thermochemical reactions, oxidation losses and the residual content of chemical elements. In this scenario, among evolutionary algorithms, Genetic Algorithms (GA) [2] proven to be an effective and flexible approach for tackling the problem as a multi-objective optimisation challenge. GAs are inspired by the principles of natural evolution (i.e. selection, crossover and mutation) and allow to explore large solution spaces without requiring strong assumptions about the form of the objective functions. As previously mentioned, the problem is described by two objective functions: (i) the economic impact, considering the costs related to the electricity consumption and materials added in the ladle, with prices that are plant specific and (ii) the environmental impact, calculated through a Life-Cycle-Assessment-based [3] methodology, focusing on the main energy and material flows of each specific heat. As previously mentioned, the optimization problem includes a set of constraints for describing the operational limits of the LF, energy consumption, additive materials to add, final chemical composition, final steel temperature, and chemical and physical numerical behaviours, represented by the NN-based models.

The DSS is equipped with a graphical user interface supporting users' interaction with the developed tools. Currently the software solution is in the phase of test before the full deployment in the plants, where extensive field tests will be conducted to prove the effectiveness of the ALCHIMIA platform.

ACKNOWLEDGEMENTS

The work described in the present paper has been developed within the project entitled "*Data and decentralized Artificial intelligence for a competitive and green European metallurgy industry*" (Ref. ALCHIMIA Grant Agreement No. 101070046) that has received funding from the Horizon Europe research and innovation program of the European Union, which is gratefully acknowledged. The sole responsibility of the issues treated in the present paper lies with the authors; the Commission is not responsible for any use that may be made of the information contained therein.

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EXPLORING THE POTENTIAL OF MACHINE VISION (MV) AND ARTIFICIAL INTELLIGENCE (AI) IN STEEL PRODUCTION

Eric Almquist – StarTool, USA

INTRODUCTION

Machine Vision (MV) and Artificial Intelligence (AI) are rapidly evolving technologies poised to transform most aspects of life, including steel production. While these technologies are already deployed in metallurgical plants — primarily to optimize process models — their potential extends far beyond conventional applications.

Many operational blind spots still exist. MV/AI enables machines to sense and respond where traditional sensor/output processes fall short.

KEYWORDS: MACHINE VISION (MV) – ARTIFICIAL INTELLIGENCE (AI) – STEEL MANUFACTURING – WORKER SAFETY – EDGE COMPUTING – PROCESS MONITORING – DIGITALIZATION

TECHNOLOGY OVERVIEW: INPUTS, PROCESSING, & OUTPUTS

The presentation will begin with a brief overview of key input sensors, such as depth cameras, thermal imaging, and LiDAR, alongside data processing options that leverage edge computing and real-time analytics. Attendees will gain insight into how these components interact to extract meaningful, actionable information.

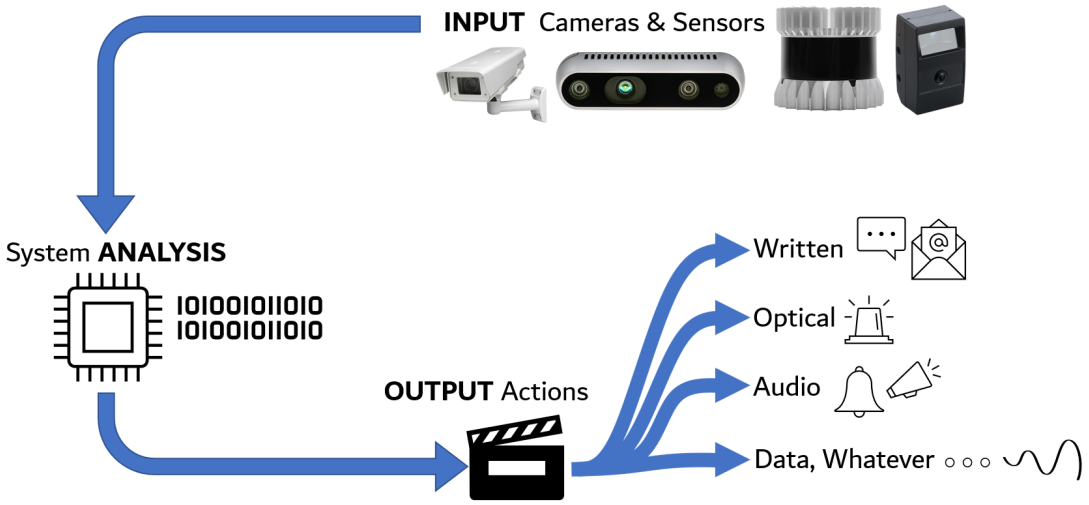

Fig.1 – Simplified Overview of Technology Components

APPLICATION EXAMPLES AND USE CASES

Building on this foundation, the presentation will highlight novel applications of MV and AI that extend beyond process control. MV/AI enables visual assessment of a physical, analog space and converts it to digitally based actionable information.

- Monitor for Workplace Hazards (e.g., collisions)
- Track Materials and Movement in Real Time (e.g., inputs, finished goods, vehicles)
- Visually Assess Physical States (e.g., valves, analog indicators, gates)
- Assist Front-Line Workers (e.g., detect/classify abnormalities during inspection)

BENEFITS, SCALABILITY, AND REALISM

As steel manufacturers seek to optimize productivity and quality, reduce waste, and enhance workplace safety, MV and AI present exciting new opportunities.

- More capable and lower cost hardware.
- Increasingly capable technology partners.
- Edge development: low latency, no cloud dependence

CONCLUSION: INVITATION TO INNOVATE

By understanding how these tools are applied attendees can begin to imagine a myriad of use-cases. This session encourages attendees to think beyond conventional automation and explore innovative solutions that could redefine the future of metallurgical manufacturing.

<END>

Transforming Steelmaking: Advanced Automation Solutions Powering the Twin Transition

Andreas Rohrhofer
Anna Mayrhofer
Primetals Technologies Austria GmbH
Turmstraße 44, 4031 Linz, Austria

The steel industry is undergoing a twin transition, where digitalization and sustainability work in tandem to drive efficiency, reduce environmental impact, and enhance productivity. As steelmaking is an energy-intensive process with significant CO_2 emissions, the integration of advanced automation solutions is essential to meet the industry's growing demands for decarbonization and resource efficiency. By implementing intelligent automation across key steelmaking aggregates, steel producers can achieve real-time process optimization, reduce energy consumption, and ensure consistent product quality.

In the Basic Oxygen Furnace (BOF), automation enables optimized process control with precise endpoint detection. Machine Learning approaches are introduced for further refinement of models, enhancing precalculation accuracy of essential process parameters. Additionally, expert systems automate operator tasks, such as converter tapping.

The Argon Oxygen Decarburization (AOD) process, benefits from new functionalities enabling dynamic adjustment of gas ratios and active temperature control, leading to cost and environmental benefits.

For Electric Arc Furnace (EAF), a new online emissions monitoring module, provides continuous reporting of emissions produced. Integrated evaluation algorithms make emissions of the furnace transparent and provide information as a basis for emission reduction. Additionally, AI-driven analytics support better decision-making, reducing variability in the melting process.

In Secondary Metallurgy (SecMet), calculating desulfurization, aluminum fading, and homogenization is challenging due to the dynamic nature of molten steel/slag movement. Traditional models calculate these parts separately, requiring extensive parameter adjustments. New Process optimization functions use a kinetic model to predict circulation movement, resulting in more precise predictions of sulfur and aluminum values.

By integrating digital technologies such as machine learning, AI-driven analytics, and real-time monitoring, steel producers can align industrial performance with sustainability goals, reducing carbon footprints while maintaining high productivity. This comprehensive approach to automation across BOF, AOD, EAF, and SecMet supports the twin transition, ensuring a smarter, cleaner, and more competitive steel industry for the future.

KEYWORDS: TWIN TRANSITION – DIGITALIZATION – SUSTAINABILITY – DECARBONIZATION – AUTOMATION – ARTIFICIAL INTELLIGENCE (AI) – PROCESS OPTIMIZATION – BASIC OXYGEN FURNACE (BOF) – ARGON OXYGEN DECARBURIZATION (AOD) – ELECTRIC ARC FURNACE (EAF) – SECONDARY METALLURGY (SECMET)

INTRODUCTION

The steel industry remains a cornerstone of modern civilization, supplying critical materials for infrastructure, renewable energy systems, and the electrification of transportation. Despite its importance, the sector faces mounting pressure to improve operational efficiency, remain competitive in a rapidly evolving global market, and—most critically—reduce its substantial carbon footprint. Currently, steel production accounts for approximately 8–9% of global CO_2 emissions [1].

To address these challenges, the concept of the Twin Transition—the simultaneous pursuit of digital transformation and environmental sustainability—has emerged as a strategic imperative. By integrating

advanced digital technologies with sustainable production practices, the steel industry can strike a balance between economic performance and environmental stewardship.
This paper explores how advanced automation technologies are enabling the Twin Transition in steelmaking. Leveraging both existing and emerging systems, steel producers are achieving unprecedented levels of efficiency and product quality. Artificial intelligence, combined with sophisticated data analytics and real-time monitoring, is driving the evolution towards fully autonomous operations. Tools such as sensors, robotics, and virtual simulation environments are being used to optimize and adapt production processes to meet the growing demand for high-quality steel.

AUTONOMOUS PLANT CONCEPT

The concept of an Autonomous Plant marks a transformative advancement in the steelmaking sector. It centers on significantly reducing the need for manual intervention by leveraging cutting-edge automation, remote monitoring, and seamlessly integrated control systems. This approach not only streamlines operations and enhances process accuracy but also reinforces safety standards—ultimately enabling a single operator to efficiently manage multiple aggregates within a steelplant.

For the metallurgical plants, autonomy levels can be derived as follow [2]

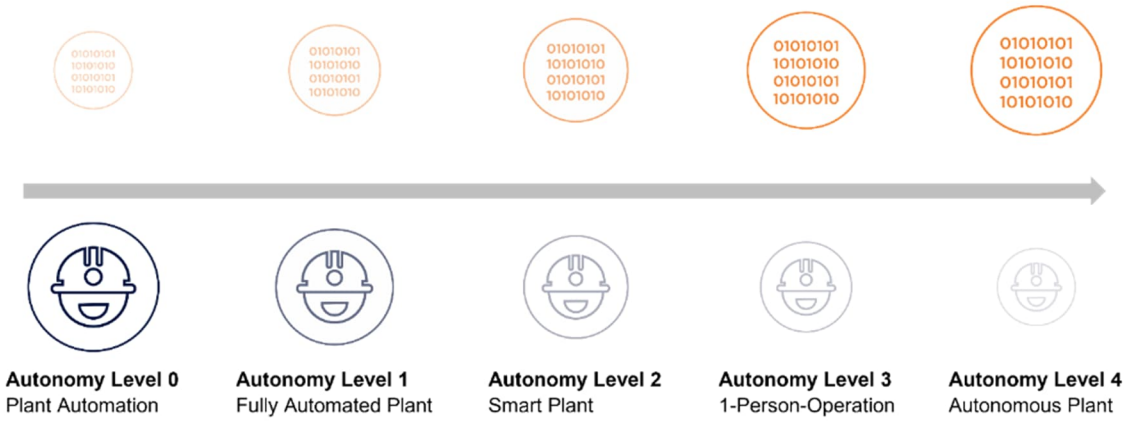

Fig. 1 - Autonomy levels of metallurgical plants

- **Level 0: Plant Automation**
  The plant is equipped with classical automation software, typically basis and process automation software. The operators are fully operating the plant themselves.
- **Level 1: Fully Automated Plant**
  In addition to the classical automation software, the plant is equipped with supervisory systems like condition or quality monitoring systems which provide more insight in plant and production. Resulting improved production rules are given to the operators who are still operating themselves.
- **Level 2: Smart Plant**
  The plant is equipped with digital assistants and expert systems; The operators are actively supported during production and the need for operator input is reduced.
- **Level 3: 1-Person-Operation**
  The plant has reached a level of autonomy where several operators can become pure supervisors of the plant and 1-person-operation is possible. In this case, the interface between operator and plant, the pulpit and its human-machine interface, needs to be revised.
- **Level 4: Autonomous Plant**
  The digital assistants have become expert systems. Standard operation and exceptions can be handled by the plant autonomously. The operators are all mainly supervisors and intervention is required only in special cases.

At the core of the Autonomous Plant concept lies the Central Operation Cockpit [3]—a smart, centralized control hub that seamlessly integrates camera feeds, traditional human-machine interfaces, and digital assistants. It delivers context-specific, streamlined information to operators, ensuring clarity and relevance at every stage of the process. For instance, camera views automatically switch based on current process steps or events, while intelligent overlays enhance visual data with real-time insights. By combining expertise in plant engineering, operations, process control, and automation, the Central Operation Cockpit enables smooth coordination across systems, making it an ideal solution for efficient and unified plant management.

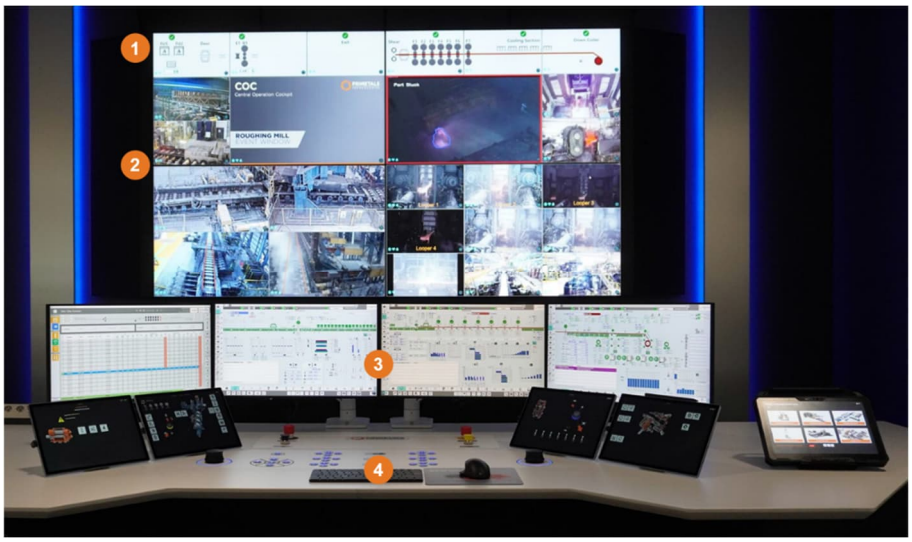

Fig. 2 - Central Operation Cockpit (COC);
1 Plant overview, 2 Camera streams for required process view or KPIs,
3 SCADA level for process operation, 4 Operating elements for manual process intervention

AUTOMATION SOLUTIONS

Automation solutions play a central role in advancing the Twin Transition, seamlessly integrating digital innovations to boost efficiency and precision while supporting sustainable practices. These technologies are key to reducing emissions, optimizing resource utilization, and driving decarbonization across the steelmaking process. The following sections introduce a range of automation solutions tailored to specific production areas, each contributing to the realization of a more intelligent, efficient, and environmentally responsible steel industry.

BASIC OXYGEN FURNACE (BOF)

The BOF Optimizer [4] from Primetals Technologies leverages dynamic simulation and advanced data analytics to enhance process accuracy and product quality in Basic Oxygen Furnace operations. By analyzing operational data, the system identifies opportunities for improvement, optimizes parameter settings, reduces resource consumption, and lowers emissions. This real-time adjustment of process variables ensures consistent performance, contributing significantly to both the efficiency and sustainability of steel production.

Feedback Calculation and Heat Data Evaluation are two essential tools in achieving these objectives. They provide the necessary insights to fine-tune process parameters, monitor performance in real time, and support continuous improvement in both efficiency and sustainability.

The Feedback Calculation tool, which is currently further developed, uses the measured and calculated data from the heats produced to improve the tuning parameters used for calculation. The tool provides the possibility to recalculate completed heats with modified tuning parameters.

In the Sandbox Mode tuning parameters can be manually selected and adapted, whereas in the Optimize Mode an optimal set of tuning parameters is calculated.
After choosing completed heats and select tuning parameters, the optimizing system calculates the respective results, which are compared to the measurements of temperature and steel analysis of the heat. With the help of Feedback Calculation it is possible to gradually improve calculation accuracy by selecting more suitable tuning parameters resulting in reduction of deviations between calculated and measured values.

To ensure the effectiveness of the Optimize Mode in the Feedback Calculation tool, a robust and high-quality data foundation is essential. This is where the Heat Data Evaluation Module plays a critical role. The Heat Data Evaluation module systematically assesses the quality of each heat by calculating a comprehensive index that reflects the reliability of process operation, input data, and model accuracy. This evaluation is crucial for identifying which heats are suitable for optimization and for building a trustworthy dataset that supports continuous model refinement. The evaluation considers a wide range of criteria, including:

- Quality of input data, such as hot metal weight and chemical analysis
- Deviations from standard procedures, for example, material additions shortly before sampling
- Completeness of measurements, including inblow and endblow samples for metal and slag
- Alignment between model predictions and actual measurements
- Occurrence of abnormal events, such as slopping or blowing interruptions

By quantifying these factors, the Heat Data Evaluation not only ensures that only high-integrity data is used for optimization but also provides process engineers and metallurgists with a fast, structured overview of key performance indicators (KPIs). This enables targeted improvements in both operational consistency and model accuracy, forming the basis for a more intelligent and sustainable steelmaking process.

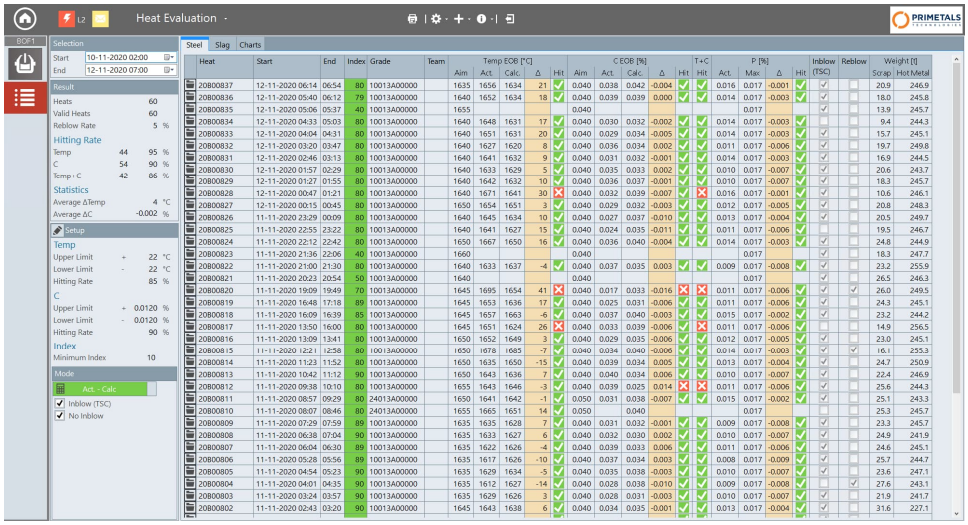

Fig. 1 - Heat Data Evaluation showing KPIs of a set of heats on the left side and the performance of individual heats on the right side

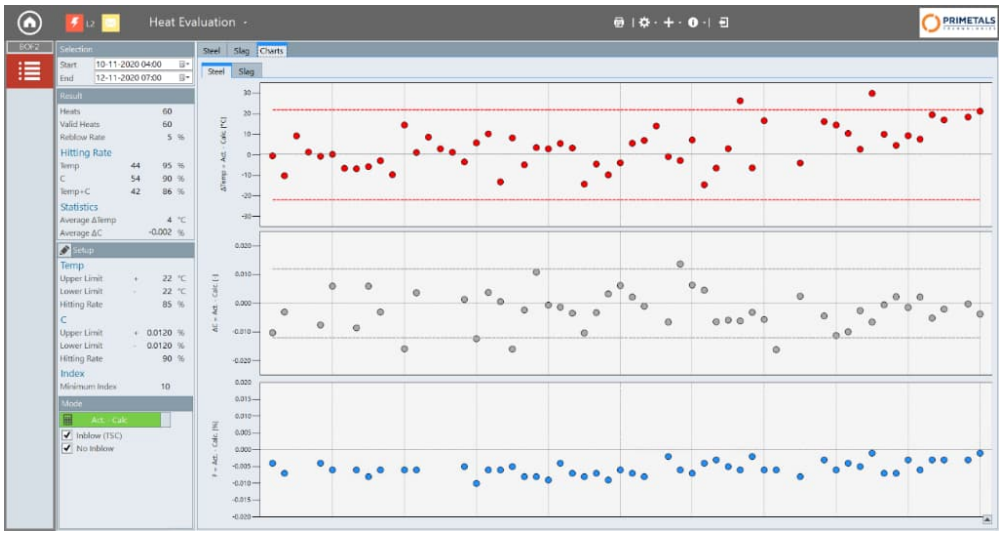

Fig. 2 - Heat Data Evaluation showing a comparison of actual values to calculated values in a graphical form

Expert systems play a crucial role in automating complex tasks and processes at the BOF [5]. One notable example is the BOF Tapping Expert, which utilizes AI-based optical imaging and smart decision-making capabilities to automate the tapping process. This system reduces human intervention, enhances operational safety, and increases productivity by ensuring precise and consistent execution of the tapping process.

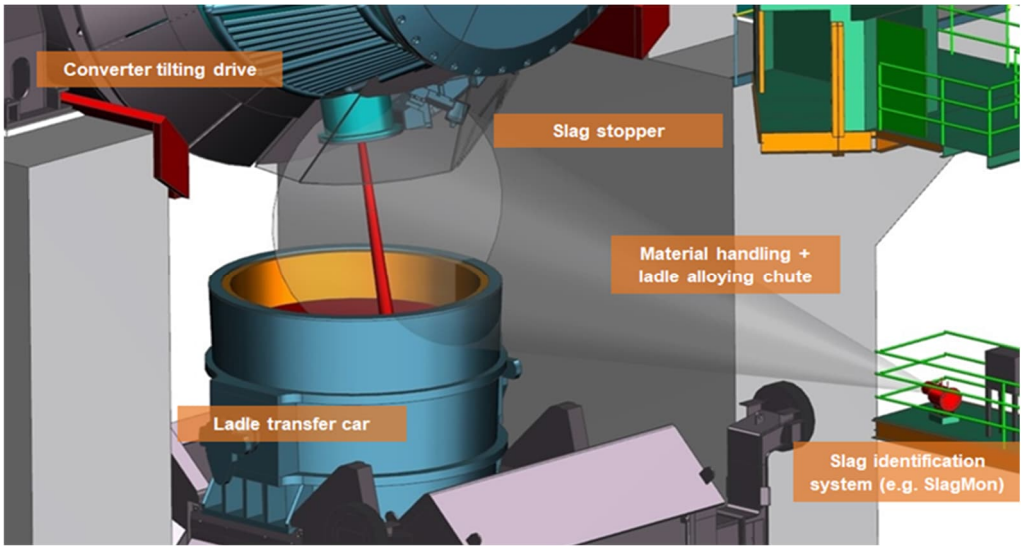

Fig. 3 - BOF Tapping Expert

ARGON OXYGEN DECARBURIZATION (AOD)

The AOD Optimizer enhances process control in stainless steel production, addressing the high variability in process conditions compared to BOF. It uses hybrid process models and first-principle calculations (mass and heat balances) to dynamically manage and optimize operations [6]. Key functionalities include:

- Charging Calculation: Determines initial metal and slag conditions, including temperature predictions for startup heats.
- Bath Height Model: Calculates bath height based on charge materials and refractory wear, improving lance positioning.
- Tapping Model: Accounts for temperature loss and nitrogen pickup during tapping.
- Desiliconization Control: Triggers and manages desiliconization phases when needed.
- Feeding Control: Divided into Alloy Control (for steel composition) and Slag Former Control (for slag properties), optimizing material additions.

- Switch Over Point Control: Optimizes the transition from nitrogen to argon to meet nitrogen targets efficiently.
- Decarburization Control: Manages carbon removal in multiple steps with intermediate targets and automatic transitions.
- Reduction Control: Minimizes Cr_2O_3 in slag to maximize chromium yield.
- Desulphurization Control: Enables precise sulfur reduction, including two-slag practices for ultra-low sulfur targets.
- Reblow Control: Automatically selects corrective blowing recipes based on deviations in temperature or composition.
- Final Adjustment Control: Fine-tunes alloy additions for direct casting readiness.

These integrated control functions support a highly automated, efficient, and sustainable AOD process.

A key factor in reducing material consumption is the implementation of the Slag Expert system. The slag composition is decisive for the chemical reactions in the converter process and the associated achievement of the target values. The main goal of the Slag Expert is the determination of required slag basicity in order to achieve the target sulfur content. With this, an optimized consumption of lime and dolomite with stable achieving of targets, especially S, is possible. In the best case a reduction of consumption figures and prevention of reblows are possible. Additionally, the amount of MgO close to saturation degree is determined, enabling protection of the lining.
Operational results from recent installations demonstrate that performance expectations have been exceeded: a reduction in lime consumption, an improvement in sulfur hit rate and a reduction in reblow rate.

ELECTRIC ARC FURNACE (EAF)

The Electric Arc Furnace (EAF) is uniquely positioned to drive the twin transition. As a flexible, scrap-based steelmaking technology, the EAF is more sustainable than traditional blast furnace routes. By integrating advanced automation, real-time data analytics, and closed loop control strategies, EAF systems are transforming meltshops into intelligent, efficient, and environmentally responsible production environments.

EAF optimization systems, such as the EAF Optimizer, are foundational to the digital transformation of steel production. These systems leverage smart sensors to create a connected, intelligent meltshop environment. Real-time data from off-gas analysis, temperature control, and material tracking feed into predictive models and closed-loop control systems, enabling autonomous decision-making and adaptive process control. This digital infrastructure not only enhances operational transparency and responsiveness but also supports remote diagnostics, simulation-based training, and continuous improvement through data-driven insights.

In the journey toward sustainable steel production, CO_2 monitoring represents a critical first step in understanding and optimizing the environmental footprint of Electric Arc Furnace (EAF) operations. As global regulations tighten and the industry shifts toward decarbonization, the ability to measure, analyze, and act on emissions data becomes a strategic necessity.

The EAF Optimizer integrates a dedicated CO_2 Monitoring Module that continuously evaluates CO_2 emissions during the melting process. This data enables operators to identify inefficiencies, and unoptimized process conditions. The CO_2 monitoring module applies methodologies aligned with ISO 14404, assigning emissions to individual heats or products. This level of granularity supports traceability and accountability, allowing steelmakers to benchmark performance.

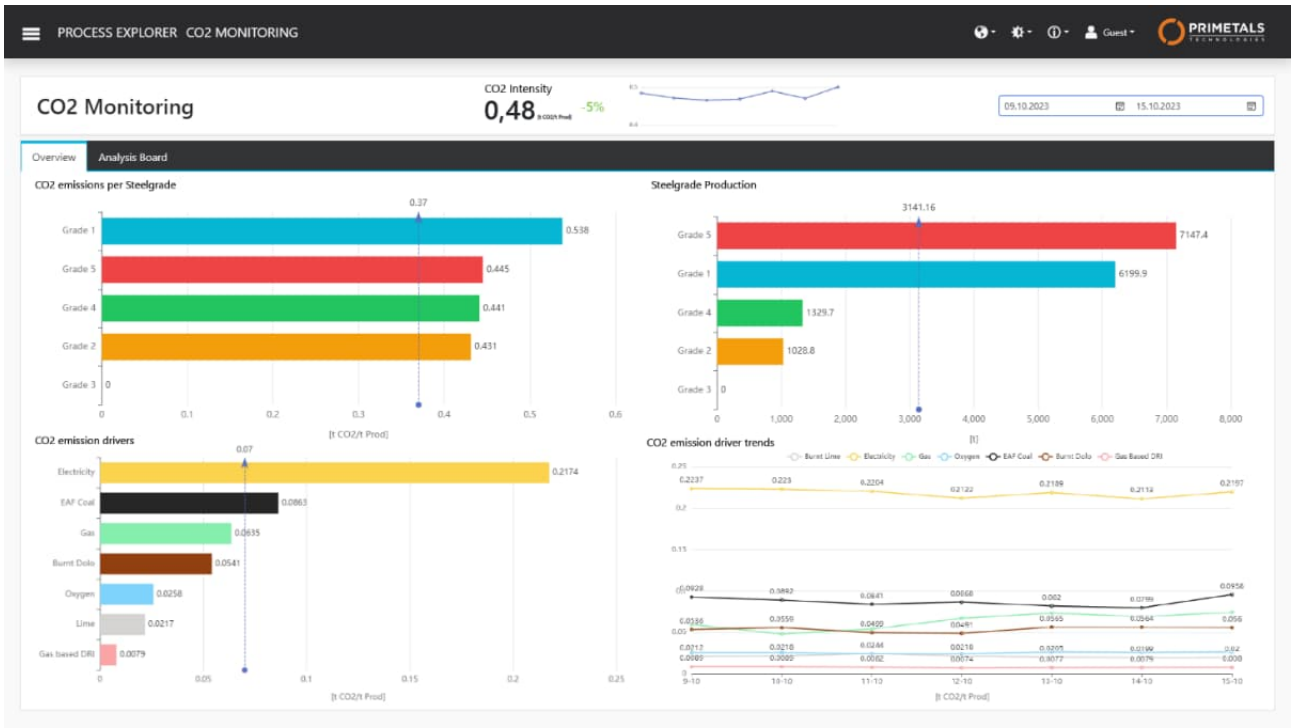

Figure 3. Visualization of the CO_2 monitoring Module

By correlating emission data with process parameters, the EAF Optimizer can guide adjustments in burner settings, oxygen injection, and material inputs to reduce carbon intensity. When combined with modules like Dynamic Burner Control and Post-Combustion Oxygen Control, the system not only minimizes emissions but also improves energy efficiency.

While CO_2 monitoring provides the essential transparency needed for environmental accountability, the next critical step is actively minimizing emissions through intelligent process control and optimization.

A significant portion of CO_2 emissions in EAFs originates from the combustion of fossil fuels and carbon-based materials. The EAF Optimizer addresses this through Dynamic Burner Control and Post-Combustion Oxygen Control, which ensure that burners operate at optimal efficiency and that flammable gases in the furnace atmosphere are fully utilized. By dynamically adjusting gas and oxygen flow rates based on real-time process conditions, these modules reduce excess fuel consumption and prevent incomplete combustion—both of which contribute to unnecessary CO_2 generation.

Another key strategy for minimizing emissions is the optimized use of carbon-containing materials, such as injected carbon. The Carbon Endpoint Control Module ensures that only the necessary amount of carbon is added to achieve the desired steel composition, avoiding overuse and the associated emissions. Similarly, Foaming Slag Control helps maintain ideal slag conditions with minimal carbon input, supporting both metallurgical performance and environmental goals.

Efficient raw material management also plays a vital role in emission reduction. The Dynamic Scrap Mix Control module calculates the most cost- and carbon-efficient combination of scrap and metallics, taking into account material availability, prices, and carbon content. By minimizing the use of high-emission materials and maximizing yield, the system reduces the carbon footprint per ton of steel produced.

Since approximately 30% of the input energy in an electric arc furnace is lost through off-gases—half as heat and half as unused chemical energy. The Lomas EAF- Off-Gas Analysis system is a critical advancement in the pursuit of optimized, sustainable, and safe electric steelmaking. It is a high-precision, in-line gas analysis system that provides continuous, real-time monitoring of the extremely hot, dust-laden off-gases generated during the EAF process. This capability is essential for process optimization and environmental performance, making it a cornerstone technology in modern meltshops.

EMPOWERING THE TWIN TRANSITION TROUGH SECONDARY METALLURGY OPTIMIZATION

Secondary Metallurgy (SecMet), as the final refining stage before casting, plays a pivotal role in this transformation. With advanced automation systems and process models, SecMet becomes a powerful enabler of both smart manufacturing and sustainable production.

Modern SecMet automation systems, integrate real-time process models, dynamic operator guidance, and advanced data evaluation tools. These systems digitize the entire treatment process—from alloying and deoxidation to desulphurization and degassing—using thermodynamic and kinetic models that simulate and predict process behavior with high accuracy. The result is a standardized, transparent, and traceable operation, where human error is minimized and decision-making is supported by intelligent algorithms. Features like proactive error prevention, metallurgical setpoint control, and historical heat data analysis empower operators and engineers to continuously improve process stability and product quality.

Secondary Metallurgy optimization directly contributes to decarbonization by reducing energy consumption and raw material expenses. Optimized heating patterns, vacuum cycles, and alloying strategies minimize the use of electrical energy and gas and reducing the need for corrective treatments. Real-time monitoring of slag conditions, desulphurization efficiency, and oxygen activity ensures that refining reactions are completed with minimal raw material input, lowering the carbon footprint of each heat. Furthermore, the ability to track and evaluate gas and energy consumption per heat supports reporting and continuous emission reduction.

By combining automation, metallurgical intelligence, and data analytics, Secondary Metallurgy becomes a strategic enabler of the twin transition. It bridges the gap between upstream steelmaking and downstream casting, ensuring that digital and environmental goals are met without compromising productivity or quality. As steel producers face increasing pressure to modernize and decarbonize, optimized SecMet operations offer a clear path forward—delivering smarter, cleaner, and more competitive steel production.

CONCLUSION

Advanced automation solutions are central to driving the Twin Transition in steelmaking, enhancing efficiency, sustainability, and reliability. The vision of an autonomous plant, enabled by condition monitoring, process optimization, and expert systems, marks a major milestone in the industry's digital and green transformation.
As digital and sustainable technologies continue to evolve, the realization of fully autonomous steel production becomes increasingly feasible. This positions the steel industry as a leader in innovation, setting new benchmarks for responsible and efficient manufacturing.
In summary, integrating automation into steelmaking offers a powerful response to the industry's challenges. By embracing digital tools and sustainable practices, steel producers can significantly improve operational performance, reduce emissions, and accelerate decarbonization—paving the way for a more sustainable and competitive future.

CO_2 monitoring transforms emissions from a passive output into an active control variable—empowering steelmakers to take informed, strategic steps toward greener, more efficient operations. It is not just a reporting tool, but a catalyst for continuous improvement and sustainable innovation. Off course, minimizing CO_2 emissions in EAF operations is a multifaceted effort that combines real-time monitoring, intelligent control, and strategic material management. But with a modern process optimization system, steelmakers are equipped not only to measure their environmental impact but to actively reduce it.

In conclusion, the adoption of advanced automation solutions is not just a technological upgrade—it is a strategic investment in the future of steel production. It enables producers to navigate the challenges of quality, cost, and sustainability while laying the groundwork for the next generation of smart, connected meltshops.

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Technology Consulting Meets Operational Excellence to Improve Steelplants Operations

Dr.-Ing. Borrmann, Lukas; Dr.-Ing. Kempken, Jens; Hüper, Thomas; Stevens, Nadine – SMS group, Germany

Steel plants operating for extended periods tend to stabilize into a steady operational state, which may not necessarily align with their peak production potential. Emerging challenges, such as rising energy costs and the task for decarbonization, necessitate a more detailed analysis and enhancement of existing operational processes integrating push and pull scenarios.

With automation, a vast amount of process information and data is already being collected. However, efficiency assessments and optimization efforts often rely solely on average values, overlooking critical variations. A comprehensive evaluation of the entire value stream along the production —supported by distinguishing between normal and unique production situations integrating special cause variations—can provide key insights into areas for operational improvement beyond the evaluation of just averages.

The combination of technological expertise, production know how with operational excellence methodologies can help identify those additional improvement opportunities.

This can be achieved through updated standard operating procedures (SOPs), identifying and controlling input variation, visual planning, and enhanced planning discipline, all of which drive significant improvements without requiring substantial capital expenditures (CAPEX).

However, bridging the gap between methodological frameworks and real-world operations integrating state of the art technological solutions remains a challenge for both consulting and operational teams.

KEYWORDS: TECHNOLOGY CONSULTING, ASSESSMENT, OPERATIONAL EXCELLENCE, DIGITALISATION, DIGITAL TWIN, CONTINUOUS IMPROVEMENT

INTRODUCTION

Challenges of European Steel Introduction

The European steel industry faces multiple challenges that threaten its competitiveness and sustainability. These challenges necessitate innovative approaches to maintain operational excellence and adapt to evolving market conditions. Key challenges include: [1] [2] [3] [4] [5]

- *Overcapacity:* The industry is facing challenges regarding exceeding production capacity, leading to inefficiencies and reduced profitability. Addressing overcapacity requires strategic alignment and optimization of resources.
- *Rising Energy Costs:* Energy expenses have been escalating, significantly impacting the cost structure of steel production. Efficient energy management and cost-reduction strategies are crucial to mitigate these effects.
- *Availability of Green Energy:* The transition towards sustainable practices demands increased reliance on green energy sources. However, the availability and integration of renewable energy into existing operations remain a significant hurdle.
- *Transformation Strategies:* The industry must adopt comprehensive transformation strategies to modernize operations and embrace digitalization. This involves rethinking traditional processes and implementing cutting-edge technologies.

- *Knowledge Transfer:* As experienced professionals retire, the transfer of critical knowledge to younger generations becomes imperative. Developing robust training and mentoring programs is essential to preserve expertise and ensure continuity.

These challenges underscore the need for a systematic approach, combining technology consulting with operational excellence, to support steel plants to navigate through this challenging times and enhance the efficiency and sustainability of their operations.

THE CONSULTING APPROACH

The consulting approach, as illustrated in Figure 1, is based on three pillars:

1) *Technology and Asset:* Cutting-edge technology forms the foundation of every production facility, ensuring optimal performance and efficiency.
2) *Operation Management and Excellence:* Continuous improvement in operations management and the pursuit of operational excellence are essential for a company's success.
3) *Human Resources Management:* The skill level and training of operators are crucial for successful operations. The overall organizational structure establishes the framework for a productive and motivated environment.

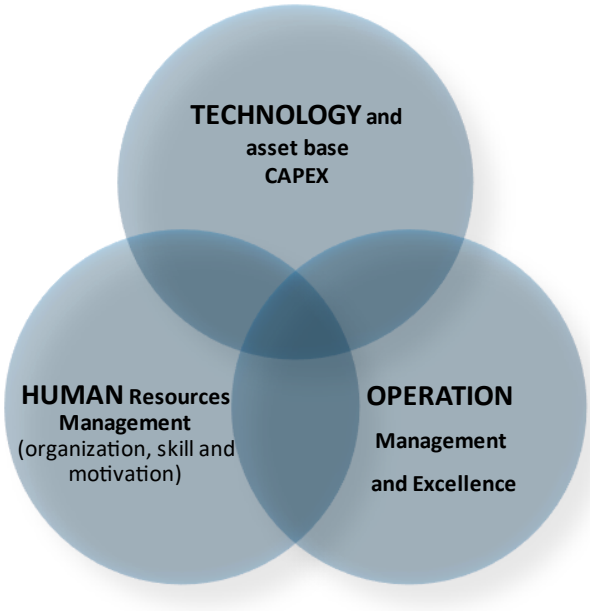

Fig. 1 – Key levers of technology consulting [6]

OPERATIONAL EXCELLENCE

Operational Excellence is a systematic approach for operations improvement. It involves the combination of advanced statistical analytics with the worldwide known and accepted methodologies of six sigma and lean management. With this a structured approach is given to establish proven cause-effect relations to than systematic improve the bottlenecks in the value stream in order to achieve the defined business targets. [7] [8]

Figure 2 illustrates the systematic journey undertaken to enhance operations through operational excellence. This process begins with the identification of gaps within current practices, followed by the development of a strategic plan aligned with the specific business objectives. Figure 2 serves as a visual guide to understanding how strategic planning and continuous methodological application leads to sustained operational excellence and achievement of business objectives.

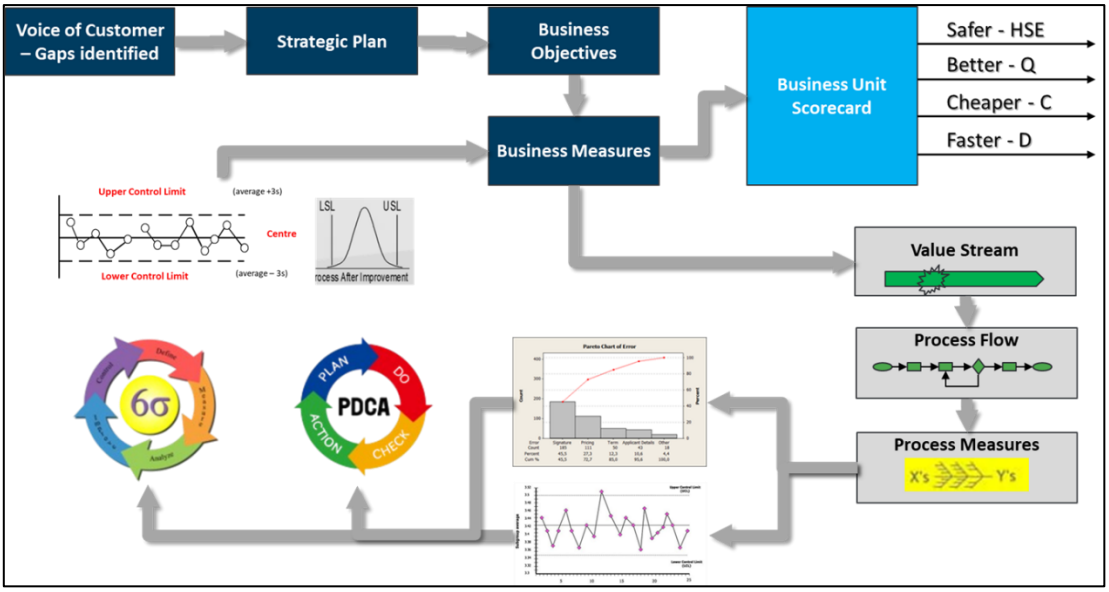

Fig. 2 – Operational Excellence Framework

The overall approach to solve any occurring challenge is structured in three phases which are always executed in different depths. The three steps of phase 1 are:

1) Preparation Phase
2) On-Site Execution
3) Post Analysis, Reporting

After having worked out the structured performance plan, the transition phase starts where the right solutions for improvement will be implemented. Quick wins and short-term improvements can directly be implemented. The third and last phase is the performance phase where continuous improvement takes place.

Fig. 3 – A structured way forward

A REAL USECASES

In this chapter the experience of several improvement projects over the last years are discussed and exemplary described.

Summarizing the experience of those projects the following challenges at optimization of integrated steel plants has been identified:

- The integrated process flow
- Various material inputs flows
- Historical evolution of plant setups and layouts
- Interaction between core and none core processes
- Plant logistics
- Skill and KnowHow loss due to changes in organization

The in step 1 collected process information is used to analyze the cycle and process times of each step within the value stream, considering especially the 2-sigma standard deviation. It is essential to evaluate not only average values but also mean, mode and standard deviations, as these provide valuable insights into the impact of special cause variations on the process chain. While the average value typically remains within a consistent range within each station of an operating value stream, this stability reflects the necessity of maintaining a steady state of the continuously running production.

The following Figure 4 shows the exemplary results of an integrated meltshop analysis, where different kind of statistical methods have been applied.

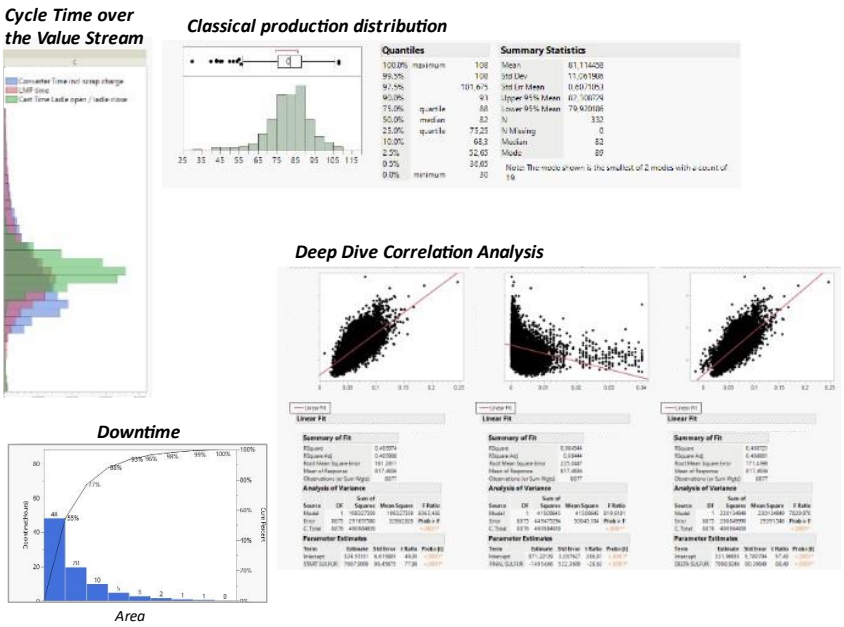

Fig. 4 – Display of various analytics approaches

The statistical results serve as the basis for formulating initial hypotheses, which will be assessed and discussed during on-site investigations. Comparisons between design and actual capacity, focusing on productivity measured in tons per hour, form the groundwork for identifying future development potential.

Concurrently, a digital twin can be developed to analyze crane movements, material flow, and additional logistical activities, alongside considerations of core equipment.

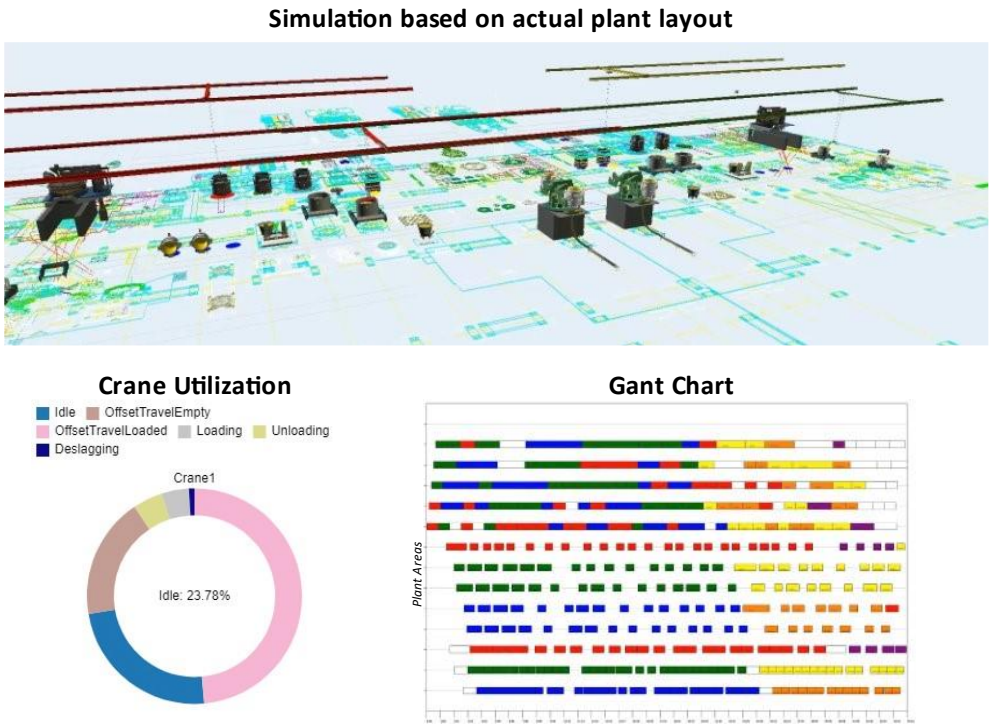

Fig. 5 - Digital twin to investigate logistical activities of core and none core processes

By investigating and relocating non-core operations, such as ladle handling, to alternate locations, potential future bottlenecks associated with increased productivity can be effectively avoided.

Integrating all gathered information, specific measures are defined to bridge the gap between current production levels and target goals.

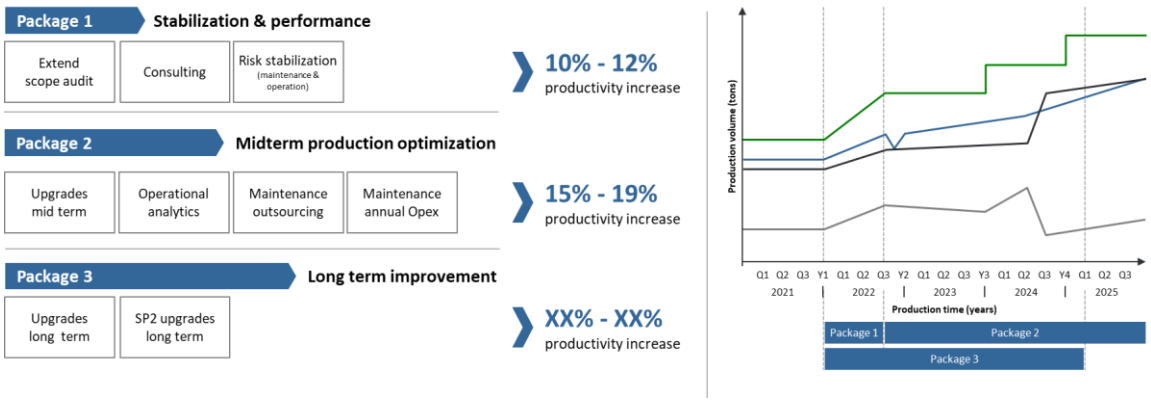

Fig. 6 – Exemplary roadmap to cover the productivity gap

Countermeasures related to operational excellence (OPEX), production organization, and capital expenditure (CAPEX) initiatives are assessed for short-term, medium-term, and long-term implementation readiness. Subsequently, these measures are evaluated as business cases, prioritized based on their return on investment (ROI).

CONCLUSION

Adapting operational excellence methodologies, originally developed for advanced industries like automotive and semi-conductor industry, to the heavy steel industry introduces unique challenges. These challenges arise due to the distinct characteristics of steel production processes and the operational environment within meltshops. Key obstacles include:

1) *Non-Continuous Process Flow:* Unlike the automotive industry, where processes often follow a streamlined and continuous flow, steel meltshops rely heavily on logistical operations to connect process steps. This intermittent flow complicates the application of methodologies designed for continuous production systems, requiring tailored approaches to address process interruptions.
2) *Data Quality Limitations:* Many older meltshops lack precise and reliable data due to outdated systems and infrastructure. Operational excellence methodologies, which rely heavily on accurate data for statistical analysis and decision-making, face limitations in environments where data quality is inconsistent or incomplete. This necessitates additional efforts in data validation and integration.
3) *Complexity of Heavy Industry Operations:* Steel production involves high-temperature, energy-intensive processes with significant variability. These conditions introduce complexities that are not typically encountered in clean industries, requiring modifications to standard methodologies to account for the unique physical and operational constraints.
4) *Integration of Technology Consulting:* Bridging the gap between advanced technology solutions and traditional steel production practices requires careful alignment. Technology consulting must address the specific needs of heavy industry, ensuring that proposed solutions complement operational excellence efforts without disrupting established workflows.

These challenges highlight the need for customized strategies and flexible methodologies when applying operational excellence principles in the steel industry. By addressing these obstacles, technology consulting can effectively support the transformation of meltshop operations, driving efficiency and sustainability.

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Energy-efficient production based on a comprehensive scheduling including an optimized temperature guidance and heat pacing

Dr. Nadine Deckert, Head Internal Quality, Jens Gellert, Expert Quality Steel Plant, ArcelorMittal Eisenhüttenstadt,
Falk-Florian Henrich, Founder And CEO, Dr. Otmar Jannasch, VP Metallurgy, Smart Steel Technologies

ArcelorMittal Eisenhüttenstadt und Smart Steel Technologies bundled forces to establish an optimized temperature guidance in the ArcelorMittal Eisenhüttenstadt meltshop. The underlying core of the supporting models, namely the Ladle Furnace, LF Temperature or Secondary Metallurgy Exit Temperature Model is a digital twin of the whole meltshop. It incorporates all heats and different steel grades, the different ladles in circulation and all aggregates in the meltshop from Basic Oxygen Furnace, BOF, via Argon Stand and Degassing Station, RH to the caster. All relevant planned and actual timestamps of all heats on their way through the meltshop as well as important process parameters are transferred via Message Queues from the L2 to the model databases. All heats including their temperatures are exactly tracked. Understanding and implementing the material flow in the meltshop including eventual disturbances and delays is crucial to build a digital twin. It is used to exactly model and recommend the hand-over temperature from secondary metallurgy to the continuous caster. The result is a precise temperature and thus, time structure for a smooth high quality production. Further, this optimization is an integral part of the newly to be installed scheduling system, the SST Scheduler. It dynamically ingests the current situation in the meltshop and recalculates the production schedule. Only this comprehensive approach enables a steel plant to exactly plan all start and ends for the individual production steps. A modern dynamic scheduling system considers both a precise timing for an energy efficient production and smooth process flow to fulfill all quality demands and delivery dates.

Nowadays cost pressure forces steelmakers more than ever to optimize their production and planning process in order to produce as cost efficient as possible at highest yield, minimal quality downgrades, transition losses or excessive reheating of slabs caused by inefficient scheduling. In order to streamline the whole production process from BOF or EAF via secondary metallurgy and casting down to the hot rolling mill it is inevitable to understand both the processes and their timings as well as quality and order requirements in every detail and model it in a digital twin. An efficient temperature guidance and overall process flow that exactly follows all these needs requires both, precise recommendations for exit times and temperatures and a fast and reliable production planning at every process step to meet the high quality and time demands of modern steelmaking for an just in-time order fulfillment.

Smart Steel Technologies modeled the times and temperatures for the complete steelmaking process at ArcelorMittal Eisenhüttenstadt in a digital twin. Different steel grades and steel groups follow different process rules. This results in different treatment durations and temperatures of the liquid steel to achieve a well-defined superheat at the continuous casting at the required time to perform high-quality sequence casting. Smart Steel Technologies ingested the steel grade related standard operation practices. Further, the actual temperatures and time stamps per heat from message queues are ingested into the underlying database. This data not only gave a great understanding of what really happens in daily production but all historical data was used to train machine learning models. In particular the following models are in operation:

- LF Heating Energy Recommendation Model
- LF Real-Time Temperature Model
- Secondary Mettallurgy Exit (or Caster Supply) Temperature Recommendation Model

All these models guide the operators of the different process stations in Arcelormittal Eisenhüttenstadt to supply heats in required time and temperature to either the next step in the secondary metallurgy or to the continuous caster. The precise temperature recommendations help to save energy on one hand and to achieve the desired superheat in the tundish on the other. The models consider the different ladles, their specific heat status, all alloys, additions, purging/bubbling and most importantly, the exact time stamps. Since all models have to perform in real time under regular production conditions the advantage of the message based real-time data ingestion is an in-time comprehensive picture on every specific heat, its treatment, temperature, chemistry, and its position including time stamps. The latter gives exact information on any deviations or delays compared to the original schedule. The models react on these deviations with an adaption of the temperature and eventually with a feedback to the scheduling system when bigger deviations may have an impact on the scheduled process flow, and thus, the production plan itself.

Production planning is crucial to fulfill all orders in prime quality at lowest costs. Therefore schedules are made under consideration of the order book, all equipment and process related constraints and, of the actual status of the whole production line. Basis for efficient production scheduling is not only order and material data as well as capacities but a deep understanding of all process steps, their bottlenecks and constraints. This includes not only the meltshop data with focus on the specific requirements of the continuous casting machine, but also data and constraints from slab yard, reheating furnace and hot rolling mill including all steel grade and geometry related process rules and limitations. Special attention is to be paid to steel grade transitions, width and thickness changes and their limitations and rules. Current production planning systems are often not even semi-automatic. Meaning that schedules are mostly created manually - this bears risks. All process, change and transition rules, process and equipment limitations as well as constraints and processing times are stored in different sheets or even only as tribal knowledge and have to be considered by the scheduler. In result, creating a schedule is not only time-intensive but often violates rules and constraints. For humans it is impossible to juggle so many contradictory KPIs and optimize them sufficiently in the planning process.

Smart Steel Technologies' SST Short-Term Scheduler creates production schedules in a fully automated fashion using a MIP (Mixed Integer Linear Programming) solver for optimized schedules. One of the inputs is the order book which is automatically converted into production orders by the SST Mid-Term Planner under strict consideration of ArcelorMittal Eisenhüttenstadt's complex rule set. The production orders can then be manually selected as work inventory and the solver automatically creates the best possible casting sequences and hot rolling campaigns within a few seconds. And this while considering the full mill specific rule set, maximizing yield and productivity with minimal transition losses.
All this is based on the data which is already ingested and cleaned for the SST Temperature Optimization. The data has to be extended to cover the down stream processes in slab yard, reheating furnace, hot rolling with the proven data structure as reliable input for the SST scheduling software.

In ArcelorMittal Eisenhüttenstadt the SST Short-Term-Scheduler is being implemented based on the reliable data structure and process understanding gained in the long-term collaboration during the temperature optimization projects. It is an automated short-term scheduling system with focus on combined casting and rolling programs, maximizing hot and direct charging and optimal usage of thermal boxes. Schedules are automatically created by the software within a minute while considering all mill specific KPIs and constraints based on a given order book. The following benefits are achieved:

- High quality in-time delivery at lowest cost
- Automated schedule generation, more time efficient planning
- Live production updates and rescheduling

- Optimized schedules based on mill specific KPIs and constraints
- Increased throughput, hot and direct charging

ArcelorMittal Eisenhüttenstadt implemented the SST Temperature Optimization which is based on a detailed digital twin that exactly models the steelmaking and casting process for achieving high slab quality by casting at the correct superheat whilst optimizing the energy input and thus, saving costs. The ongoing implementation of the SST Short-Term Scheduler uses the exact same digital twin which provides reliable data on all relevant time stamps in the process and deviations between planned and actual production.

State-of-the-art software architecture in combination with MIP is the key for a modern production planning in order to meet the high demands for a high-quality, in-time production at reasonable costs.

A continuous flow model for long-term production scheduling and reactive replanning

A. Wolff[1], C. Nölle[1], J. Brandenburger[1], E. Sirovnik[2], D. Müller[2], C. Schirm[2]
[1]VDEh-Betriebsforschungsinstitut GmbH (BFI), Düsseldorf, Germany
[2] thyssenkrupp Rasselstein GmbH (RAS), Rasselstein, Germany

In the steel industry, most companies compete nationally and internationally, with prices driven by competition. To increase their profits, they must reduce their production and distribution costs. Those who are unable to adapt risk losing their competitiveness. Effective resource scheduling is essential for boosting production and minimising completion time. However, most scheduling problems are NP-hard, making solutions exponentially complex with size. Steel production scheduling is particularly challenging due to its multiple steps, resource requirements, and disruptions such as breakdowns and cancellations. This paper introduces an efficient continuous flow model for long-term production scheduling, capable of estimating a one-month production timeline and material mix to meet targets. It is fast enough to update plans as factory conditions change quickly.

KEYWORDS: PRODUCTION SCHEDULING – DYNAMIC PLANNING – HIERARCHICAL PLANNING SYSTEM – CONTINUOUS FLOW MODEL

DynReAct Platform

DynReAct PDP is an innovative pilot and demonstration project that builds upon the foundation laid by the earlier DynReAct research initiative. This pioneering effort focused on the development of an advanced and highly integrated Production Planning System tailored explicitly for the steel industry.

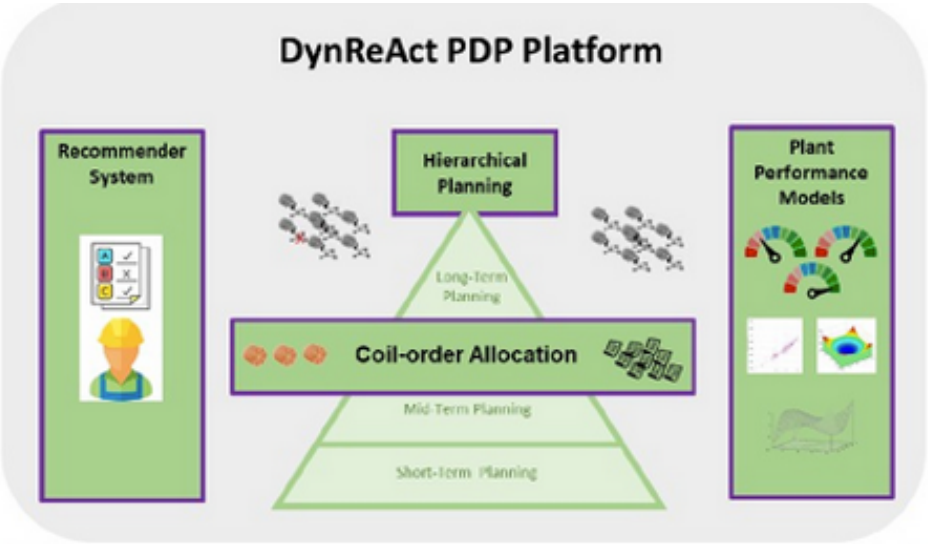


Fig.1 DynReAcT PDP Platform

The system leverages a comprehensive array of available data sources to adapt to real-time production conditions dynamically, enabling predictive analytics to anticipate potential issues or bottlenecks before they arise. The DynReAct PDP effectively demonstrates the significant benefits of dynamic production planning

through a large-scale industrial prototype, tackling the complexities associated with broad implementation across diverse manufacturing environments. Its primary goal is to design resource-efficient production plans that maximise operational efficiency while ensuring the highest possible quality standards. To achieve this, an open-source Service-Oriented Architecture (SOA) platform has been developed, as shown in Figure 1, which facilitates the generation of valid and optimised routings for the entire production process across all plants. This modular platform offers exceptional flexibility, allowing seamless integration of various planning components and algorithms. The heart of the platform is rooted in the hierarchical planning system derived from DynReAct, which uniquely combines three distinct planning horizons—short-term, medium-term, and long-term—to provide comprehensive coverage. This structure enables rapid responses to unforeseen events such as machine breakdowns or sudden order cancellations, while also supporting medium- and long-term strategic planning to ensure sustained operational efficiency and adaptability.

In this talk, we will delve into the long-term planning module in detail, discussing its various features, functionalities, and how it can be effectively utilised for strategic planning.

ACKNOWLEDGEMENTS

The work described in the present paper has been developed within the project entitled “Roll-out refinement of production scheduling through dynamic product routing, considering real-time plant monitoring and optimal reaction strategies” (Ref. DynReAct PDP Grant Agreement No. GA-101112421) that has received funding from the Research Found for Coal and Steal of the European Union, which is gratefully acknowledged. The sole responsibility of the issues treated in the present paper lies with the authors; the Commission is not responsible for any use that may be made of the information contained therein.

CASE STUDY ON PRODUCT QUALITY MANAGEMENT ON A CONTINUOUS GALVANIZING LINE THANKS TO DIGITAL SOLUTION

Maxime MONNOYER – Fives KEODS, France
Raphaël WALGER – Fives KEODS, France
Michele MANARESI – Marcegaglia Ravenna SpA, Italy

Fives' Eyeron® is a digital solution aiming at managing the quality of steel products in real time. This solution can be deployed either on a single line or in a fully integrated plant. Thanks to its effective data injection and powerful and customized rules engine system, it can automatically provide precise quality grading and reports, and issue recommendations for order reallocation or repair of any type of steel product. This innovative software optimizes quality control efficiency, reduces operational risks, and enhances overall product reliability. Installation of Eyeron® was successfully completed on the Continuous Galvanizing Line n°4 of Marcegaglia Ravenna SpA and is under deployment to the full cold rolling plant based on a strong partnership between Marcegaglia quality department and Fives. This paper will present results observed after a test period of few months.

KEYWORDS: SOFTWARE – QUALITY MANAGEMENT – DATA MANAGEMENT – GALVANIZING – INTEGRATED PLANT – AUTOMATIC GRADING – RULES ENGINE – MACHINE LEARNINGS

INTRODUCTION: EYERON® SOFTWARE

Quality engineers and production managers are facing numerous challenges since past few years due to the introduction of more and more complex products, processes, and equipment in steel processing facilities, which also strengthens the need for operational flexibility. Meanwhile, quality requirements from end customers are becoming more stringent, cost reduction remains a challenging requirement and predictive maintenance must be ensured.
Such considerations highlight the reasons why new digital tools generate lots of interest as they aim to help steelmakers improve their efficiency in terms of:

- Product development, qualification, and quality grading
- Process robustness and repeatability
- Customer claims management and defect root cause analysis
- Process deviation analysis, productivity optimization, maintenance planning and cost reduction

Based on its strong metallurgical background, Fives developed a smart quality management system called Eyeron®, that captures steelmaker's know-how rules and applies them to every production and at any stage, from steelmaking to finishing lines [1-4]. It allows comparing acceptable process ranges, customer requirements, line signals and measured product properties (chemistry, mechanical properties, surface defects) in real-time to raise alarms in case of process or product deviations and automatically qualify products according to best operator's practices immediately after production. Based on such grading, it also provides recommendations for product repair or final order reallocation.
Tracking all process steps, quality events and product information from the melt shop to finishing lines makes it also possible to ensure a precise and reliable product legacy follow-up, making comparisons between upstream and downstream signals and/or defect maps and performing automatic defect prediction, defect root cause or process drift analysis based on powerful AI models.

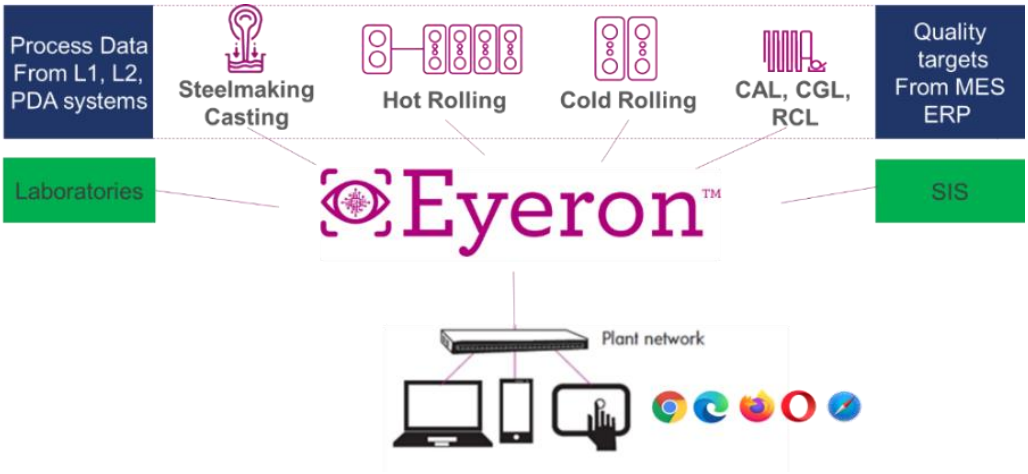


Fig.1 – Eyeron® data collection & display architecture

Among other fully customizable modules and tools are also:

- SPC module
- Customizable automatic reporting function (quality KPI, production summary…)
- Web-based application

Fives' Eyeron® has been deployed on several carbon and stainless-steel production sites in Europe and Asia, with an observed impact of 60 to 70% time saving in qualification. This also allowed for up to 20% reduction of scrap and downgraded product rate and 25% claim reduction.

CASE STUDY: MARCEGAGLIA RAVENNA SPA

Presentation of Marcegaglia Ravenna SpA.

Marcegaglia has set up its by far biggest steel metallurgy plant in Ravenna, as well as the nerve-center for integrated logistics to supply each production and distribution facility of the industrial group. The complex hosts technologically advanced equipment for carbon steel coils finishing including chemical pickling, cold rolling, annealing, skin-passing, galvanizing and pre-painting, and a service center for slitting and cut-to-length. The plant employs 885 workers.

Fig.2 – Overview of Marcegaglia Ravenna SpA. plant

At the present time, Marcegaglia Ravenna SpA. is supplying hot rolled coils from the international market. However, after the acquisition and upgrading of a new steel production site in Fos-sur-Mer (France), Marcegaglia will be able to transform its own hot rolled coil production.

Product quality management software implementation project

In 2018, Fives supplied to Marcegaglia Ravenna a first beakthrough digital solution called Smartline™, a fully automatic control system for enhanced coil processing. The solution has been installed on four galvanizing lines and has been delivering outstanding results since 2021 in terms of quality, productivity and raw material savings [5-10].

Following this, Marcegaglia aimed to upgrade its quality control systems to account for stringent customer requirements in terms of quality level and control. In fact, due to a wide upstream diversity and a multitude of end customer requirements, Marcegaglia was looking for an intelligent solution to ensure the best quality and substantially reduce the rate of downgraded coils. The project to implement Eyeron® throughout the Ravenna plant was thus initiated.

The project consisted of several key phases. The first phase of the project, so-called trial phase took place between 2023 and 2024, when a pilot solution was implemented on the Galvanizing line n°4 (CGL4). Main goals for of this phase were to confirm Marcegaglia's needs and align Marcegaglia and Fives teamwork, in order to show strong KPI to Marcegaglia top management.

In addition to the basic functionalities of the quality management software, the pilot phase enabled the development of specific functions answering particular needs of Marcegaglia:

- Data collection from 3 different sources (PDA – Process Data Acquisition system, MES – Manufacturing Execution System and SIS – Surface Inspection System Parsytec) with an so-called Injector program. The injector transforms the data of each source for each coil in a file readable by the software
- Installation of the software with its database
- Configuration of rules in order to get a grading score on 5 groups of criteria (process parameters, product parameters, surface quality, chemical composition and mechanical properties) for each coil
- Development of specific functions, in particular MSQI and Real time process alarms.

Basic functionalities

The following pictures illustrate representative basic functions of the quality management software.

First one is the product page, listing the different coils produced on the CGL4, sorted by date and providing main product information such as ID, steel grade, size and, most important, automatic grading result (global grading and detailedl grading score per criteria group. From this page, it is possible to filter products according to any characteristic, signal level, grading result, etc. Once connected to more than one process, this page will allow also to navigate between the different processes to access their specific production results.

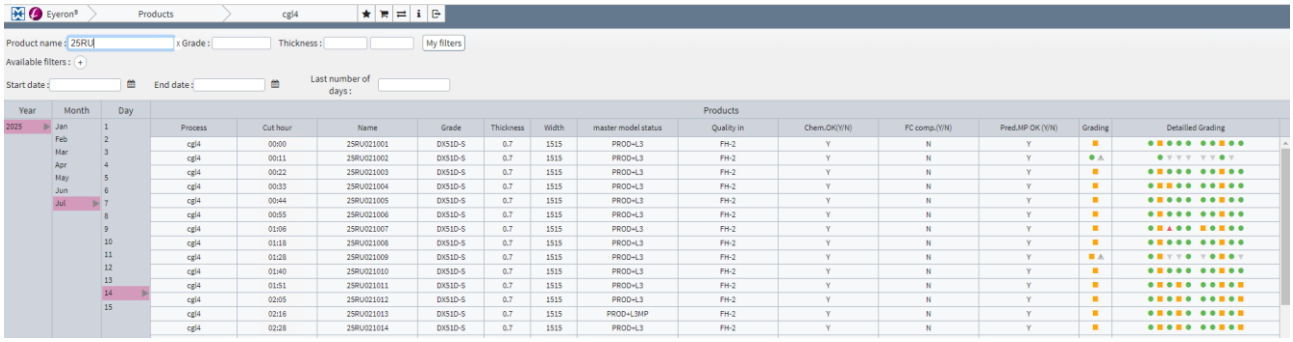
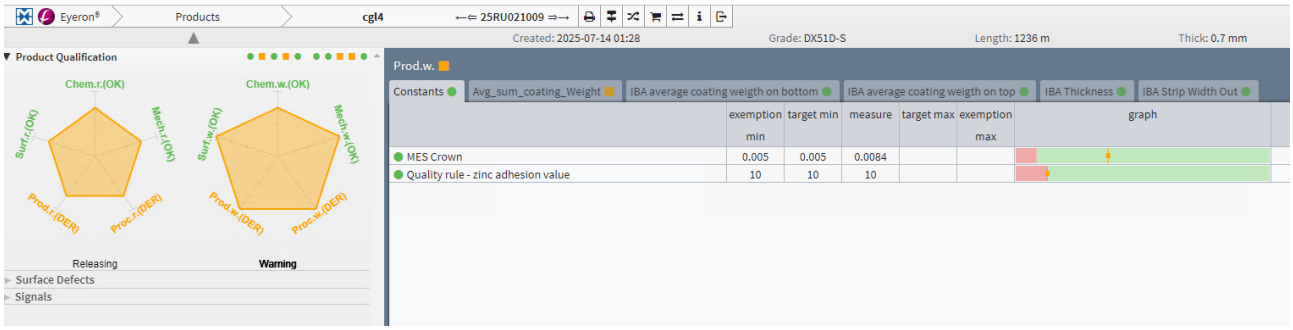


Fig.3 – "Products" page

Once clicking on one specific product, detailed information is available. All signals related to this product can be displayed, based on product length, and superimposed to each other. Even upstream (when available) and downstream signals can be seen together, with automatic adaptation of length change (elongation) and consideration of cuts, scrapping, head-tail inversion etc. Specific data such as mechanical properties, chemical analysis, product defect map from SIS and qualification results can be accessed as well.

Fig.4 – Individual product page with signals display (here, 3 coil temperatures in the CGL furnace)

Following screen presents different quality grading results examples for a given product. On the left hand side, the 5 grading criteria groups are displayed on a graphical, user friendly way, with the global grading results indicated by the colour (here orange, corresponding to “coil to be checked). On the right hand side, first example shows the grading result for fixed signals (crown level and zinc adhesion quotation). Second example shows the grading result for a variable signal (coil thickness). In each case tolerances are indicated by a colour code green - qualified/orange – derogation/red – non-qualified. Different tolerances can be defined in the grading rules depending on the position along product length.



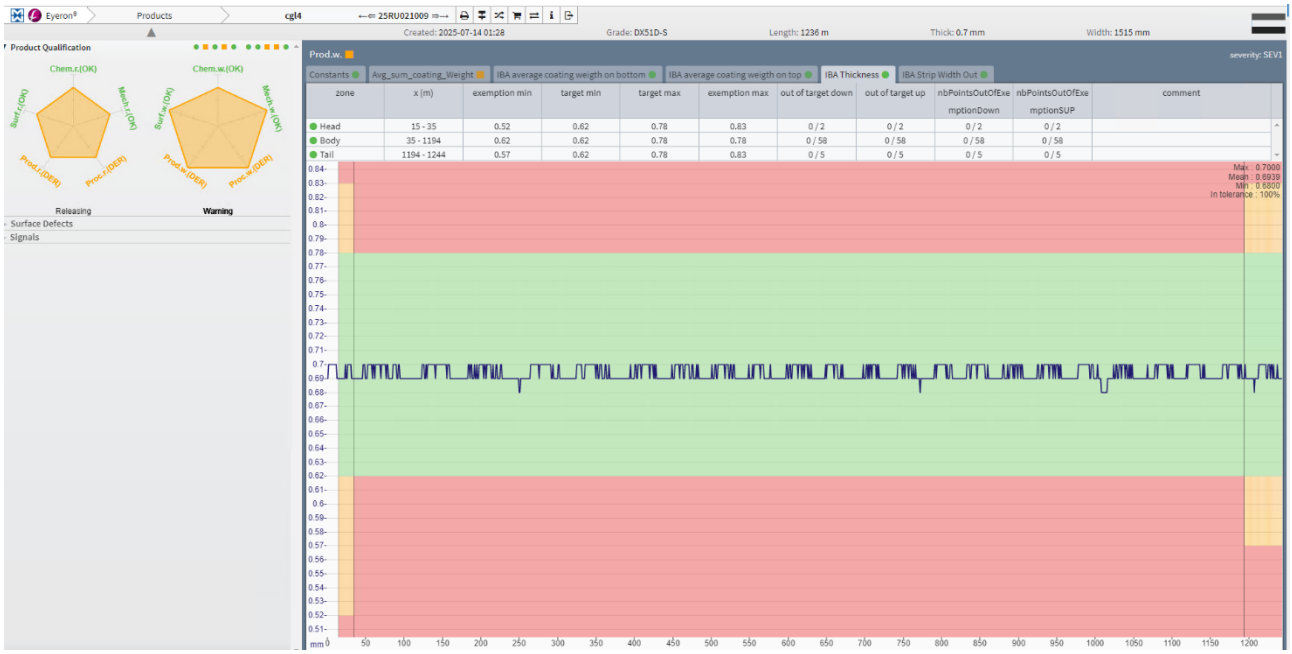


Fig.5 – Standard coil grading (with tolerances per product over the length) for fixed signal and variable signal

MSQI (Marcegaglia Surface Quality Index)

MSQI is providing a graphical representation based on a continuous signal expressing the surface quality of each product, for the whole length of the coil. MSQI signal is calculated according to following formula, for each meter of length, and can be filtered by individual defect class or by group of defects:

$$MSQI = \frac{\sum_{i=1}^{n} d_i I_i^G I_i^D I_i^P I_i^F}{Width * Unit\ of\ length} \qquad (1)$$

Where, for each defect class i:

d_i = number of defects in each unit of length

I_i^G = Gravity index depending on defect class

I_i^D = Defect distribution index depending on the standard deviation of defect position from the edge

I_i^P = Defect position index depending on the defect distribution over coil width

I_i^F = Face index depending on the quantity of defects on each product side

At the end, MSQI will be representative of the global surface quality state evolution over coil length, and can be used for very precise product quality grading. Figure 6 presents the evolution of MSQI for a given product, with the different thresholds (qualified/derogation/non-qualified). According to the signal, the product shown in the example will not be qualified.

Figure 7 presents the superimposition of a defect map, corresponding MSQI signal evolution and another process signal (strip temperature). It can be useful to superimpose defect maps, MSQI signal and process signals, for example in order to perform investigations on defect rootcauses.

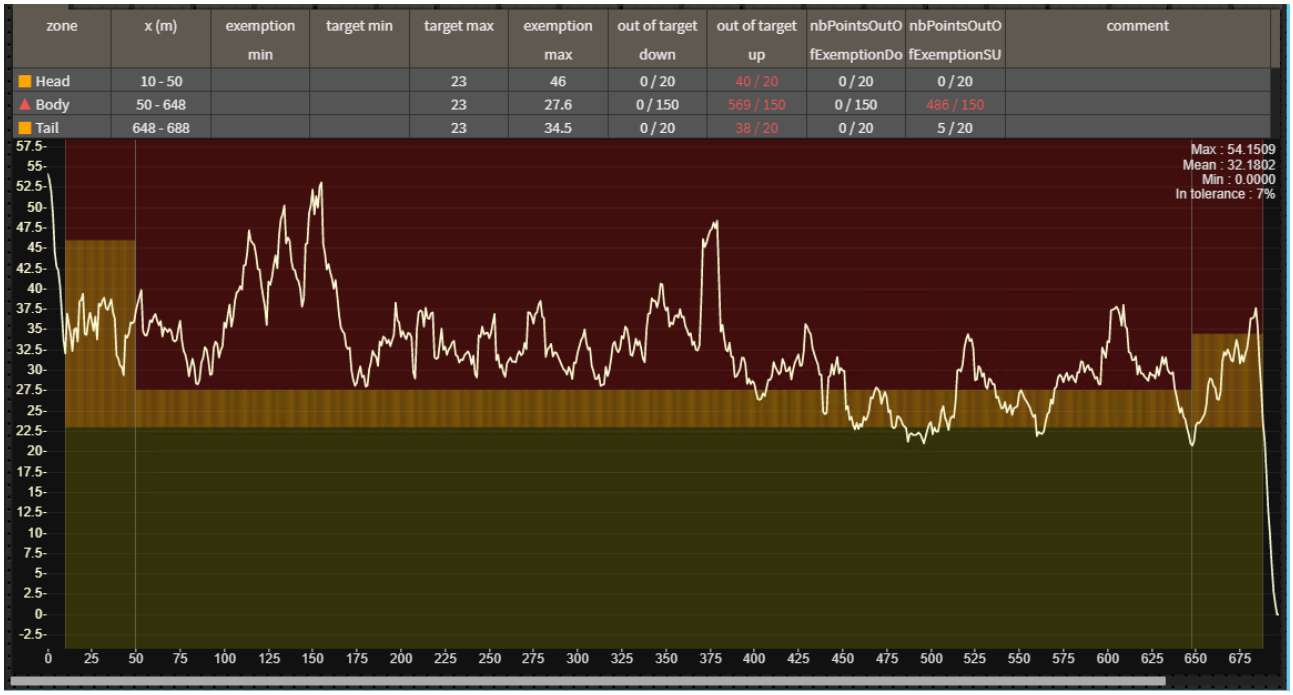


Fig.6 – MSQI signal example

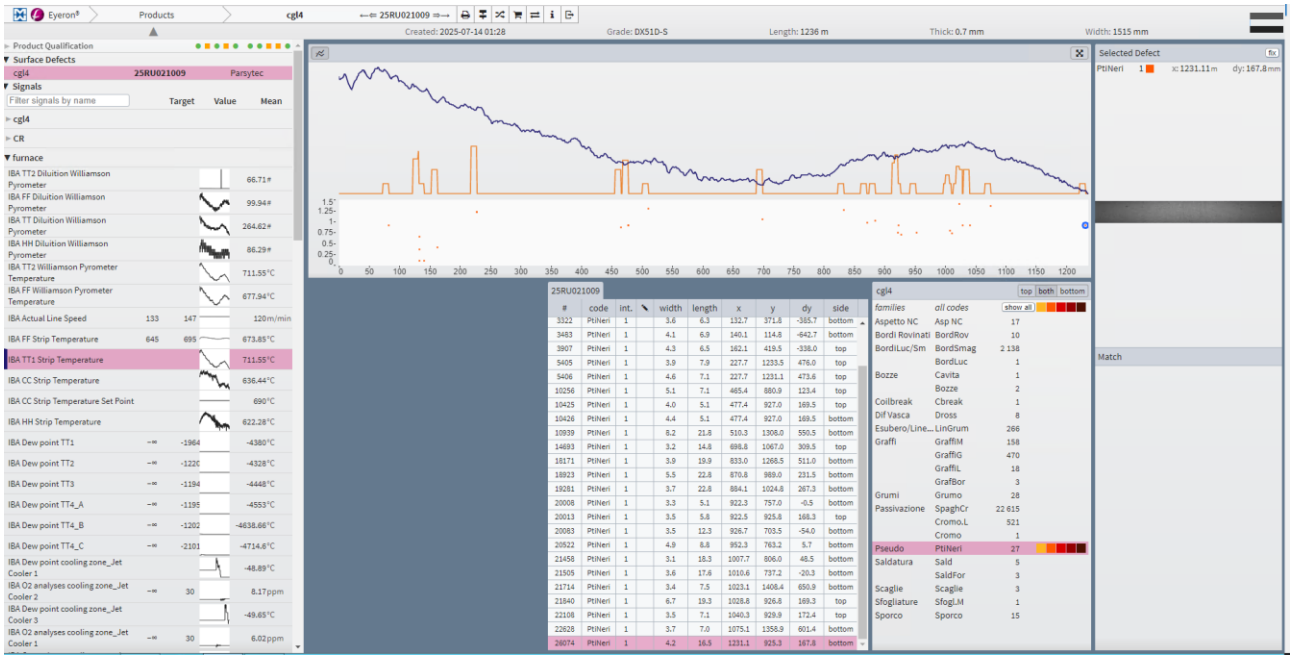


Fig.7 – Defect map with superimposed signals (MSQI & Strip temperature)

Real-time process alarms

Generation of real time process alarms allows operators to correct quality deviations as soon as they appear and increase the number of first-time, first-choice coils.

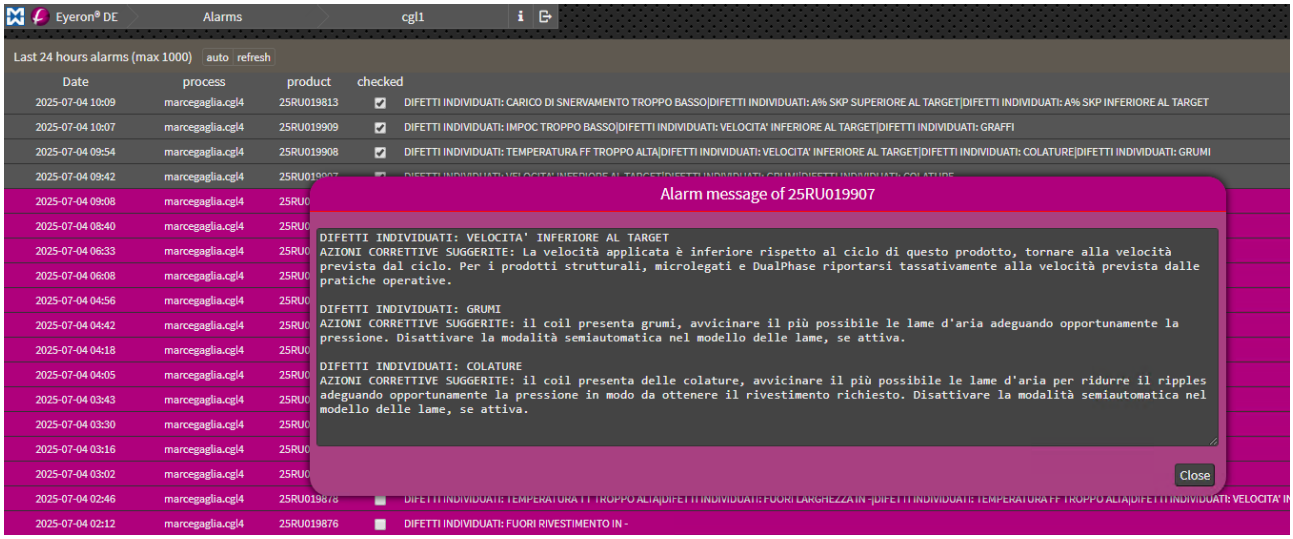


Fig.8 – Real time alarms, with Alarm details

CONCLUSION AND PERSPECTIVES

Thanks to the collaborative environment shared with Marcegalia Ravenna's quality and IT departments, it was possible to fully customize Eyeron® to steelmaker's benefit. Thus, at the end of the trial phase on CGL4, following benefits could already be identified and highlighted by Marcegaglia quality department:

- **Enhanced Reliability in Quality Control:** significant increase in the reliability of quality control across all product characteristics, including dimensions, product & process properties, surface appearance, mechanical and chemical properties thanks to customized grading score.
- **sComprehensive Process Monitoring:** improved process reliability by continuously evaluating key parameters to maintain optimal performance and compliance.
- **Proactive Approach with Smart Alerts:** proactive strategy could be implemented through an advanced alert system that prevent classifying products into non-conformities, by notifying operators as soon as a process parameter goes out of its range of acceptance.
- **Corrective Action Guidance:** the system not only identifies potential quality issues but also suggests corrective actions to quickly resolve them, minimizing disruptions.
- **Reduction in Non-Conformities and Disputes:** significantly decrease of internal non-conformities and customer claim by ensuring consistent product quality and early detection of deviations.
- Advanced Deep Failure Analysis (next step): This system will enable the implementation of deep failure analysis using advanced machine learning algorithms to further enhance quality assurance and predictive maintenance.

The project is now moving into the second phase, which involves:

- Operators training to adapt the solution to their needs so as to achieve the maximum benefits the software has to offer.
- Data collection to integrate remaining set of processes available at Ravenna site, which includes: 3 remaining CGL, Skin-pass mill, 3 cold rolling mills, 2 pickling lines
- Rule enforcement and dashboard customization for the entire plant to consolidate process and quality-related information on a single device. Thanks to trial phase, Marcegaglia is now able to implement by themselves new quality rules in dedicated rule flow.
- Development of new functions dedicated to Marcegaglia needs:

Dashboard: a new module will be created to monitor the products on each line. This dashboard will be used by line operation manager and quality department. The aim is to show the latest coils produced and to inform

the user if some consecutive coils have the same “non-qualified” grading score. The final goal is to overview the overall production, avoiding repeating deviation of process parameters on a given batch of coils.
Advanced Deep Failure Analysis: this module will use advanced machine learning algorithms to further enhance quality assurance and predictive maintenance.

The overall schedule of second phase is 15 months.

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THE USE OF IMAGE DATA IN STEELMAKING – A SHORT GUIDE TO PROMISES AND PITFALLS

Christine Gruber, Florian Egger, Sandro Russi, Maria Thumfart, Johann Wachlmayr, Klemens Winkler, Xiaomeng Zhang – K1-MET GmbH, Austria
Bernd Kleimt, Birgit Palm – Betriebsforschungsinstitut GmbH, Germany
Madalina Rabung, Frank Leinenbach – Fraunhofer Institute for Nondestructive Testing IZFP, Germany
Jean-Philippe Andreu, Harald Ganster – Joanneum Research Forschungsgesellschaft mbH, Austria
Dietmar Gruber, Chair of Ceramics, Montanuniversität Leoben, Austria
Stefan Groenheide – SPECTRAL INDUSTRIES, The Netherlands
Markus Chromy, Matthias Farveleder, Paul Oberhumer, Bernhard Voraberger - Primetals Technologies Austria GmbH, Austria
Aidong Hou, Ulrich Marschall – RHI Magnesita GmbH, Austria
Bernard Ennis, Frank Schrama, Frenk van den Berg – Tata Steel Nederland Technology B.V., The Netherlands
Raimund Fritz, Ludwig Nocke, Roman Rössler – voestalpine Stahl GmbH, Austria

Images are a very powerful tool in monitoring complex processes in industrial settings and indicating relevant events with impact on process quality and stability. The intuitive interpretability of an image is often superior to the extraction of numerical key performance indicators based on multiple data streams from a variety of sensors, but not every relevant process aspect can be directly monitored in form of images, and not every image data stream can receive attention from an operator with sufficient process experience. Therefore, automatized image processing methods for process surveillance, optimization and control are in high demand. The key challenges for successful image-based process monitoring in the steelmaking industry are inaccessible environments with often rough conditions, high demands on the timing of data acquisition and analyses, and the complex interplay of many factors influencing an outcome of a process. Even after a successful development of image acquisition solutions, the obtained data needs to be evaluated sensibly, and correct conclusions need to be drawn for the process, which might involve further knowledge from process models or experience. These questions will be discussed with examples from steelmaking: optical camera and LIBS sensor for scrap characterization on trucks, thermal and laser measurements for converter hat wear estimation, and optical camera for recirculation flow surveillance in an RH vacuum chamber.

KEYWORDS: IMAGE DATA – IMAGE PROCESSING – STEELMAKING – PROCESS MONITORING – SCRAP CHARACTERIZATION – CONVERTER VESSEL WEAR – RUHRSTAHL-HERAEUS DEGASSING

INTRODUCTION

In this contribution, we discuss important challenges in the use of image data in steelmaking using three exemplary applications: the prediction of scrap content and composition via a combination of optical and LIBS (laser-induced breakdown spectroscopy) sensors in the Horizon Europe project DiGreeS, the evaluation of converter vessel wear based on thermal and laser image acquisition in combination with finite element wear simulations in the Austrian funded ECO2LIFE project, and the assessment of stirring efficiency and homogenization degree in a Ruhrstahl-Heraeus degassing plant through the combination of image and process data, as investigated in the Austrian funded OpTwinFlow project and the Horizon 2020 project INEVITABLE. There are several important questions to answer when employing visual means of analyzing an industrial process (Figure 1), to be discussed for the three use cases separately and in connection.
There are some general rules and strategies that can be applied to image analysis problems in industrial applications, even though use cases might differ at first sight. Imaging can be done in different forms, utilizing different ranges of the optical spectrum, from the visible to other wavelength regimes, wide or narrow frequency bands (e.g., laser) and applying different capture methods and post-processing, i.e., point measurements or sweeping grid measurements to reconstruct surfaces. Also data on temperatures or other material properties can be represented as an image and analyzed as such. Depending on the problem under consideration, different approaches can be chosen to lead to a meaningful analysis of and impact on an industrial process.

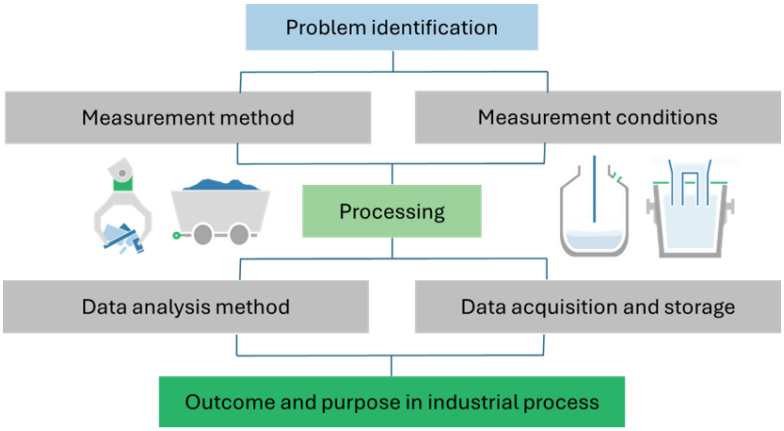


Figure 1 – Strategies for successful image analysis in industrial contexts.

PROBLEM IDENTIFICATION

Scrap characterization is an increasingly important challenge for the metals sector, in particular in face of the widespread transformation of production processes towards the use of scrap and electricity throughout Europe, which is expected to increase the demands on correctly classified and sorted scrap significantly. Scrap characterization on trucks at the point of delivery to the plant is one possibility to gain knowledge on scrap composition and quantities. Requirements for such an application are a fast and thorough evaluation of the scrap content accessible to the measurement and extrapolation to the chemical composition and quantity of the complete scrap load, directly on the truck, on the order of minutes. A combination of an optical camera for object recognition and a LIBS sensor for chemical composition can be used for this purpose. In other applications, multispectral camera imaging or x-ray-based measurement methods can also provide the necessary information on chemistry or in general, type and properties of scrap pieces, and can be used at different sites in a plant, like scrap storage areas or conveyor belts.

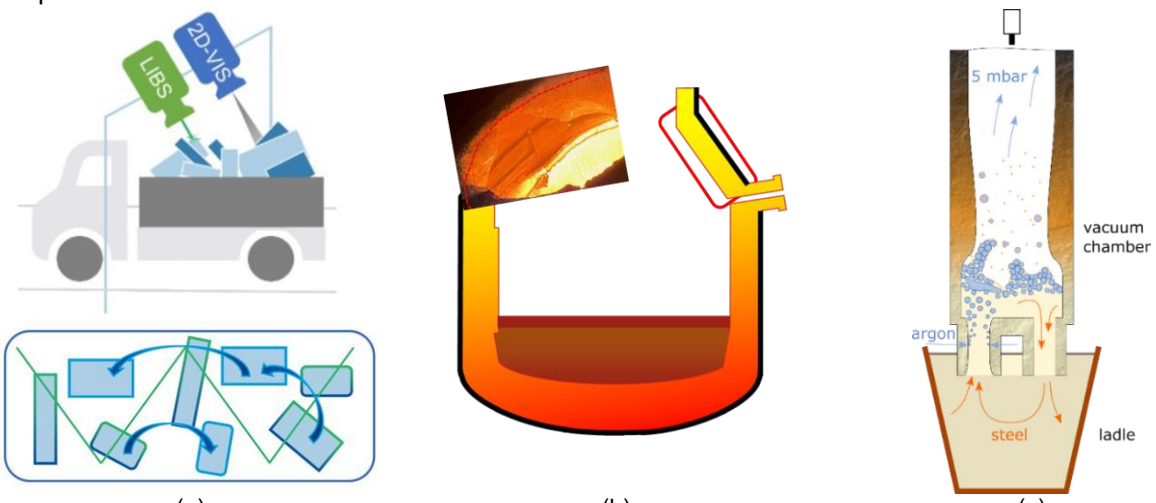
In the case of primary metallurgical aggregates such as the **basic oxygen furnace (BOF) converter**, process and plant surveillance is important to guarantee safety and stability in process operation. Visual methods of different kinds can be used to evaluate the state of the vessel and lining material, and together with numerical modelling and the analysis of process data, the best strategies for lining maintenance and process scheduling can be defined. In this use case, an optical system with a pulsed laser beam transmitted via a rotating mirror system (LaCam) is used, generating a three-dimensional image of the vessel's inner surface based on the laser triangulation measurement data. Complementary to this, an infrared (IR) camera will be used to provide information on the thermal state of the vessel shell. Both data sets are used for the validation of numerical models based on thermal and mechanical simulations of the vessel and lining material, and the results together with further process data like point-like temperature and strain measurements and vessel age serve to optimize maintenance measures during process operation and extend lining and vessel shell lifetime.

Another important steelmaking process is **RH degassing**, where liquid steel is refined and cleaned of undesired gases and chemical elements. There, optical cameras are commonly used in process surveillance to provide an image to the operator and support decisions during process operation, guiding human input to process control for safety aspects. An automated analysis of images has the potential to extract information on the process dynamics and efficiency beyond safety concerns and can be used for an optimization also in terms of time, energy, and resources used in the process. Some investigations with high-resolution, high-speed cameras have shown a far more complex behavior of the liquid metal flows in the chamber than expected from models and previously observed [1] [2] [3]. A graphical representation of the use cases is shown in Figure 2.

MEASUREMENT METHODS AND CONDITIONS AT THE MEASUREMENT SETUP

Many applications in the metallurgical industry face harsh environmental conditions or strong barriers for process observation. Processes usually take place behind thick walls or robust shielding, and involve high temperatures, dust, and physical strain, like in the use cases at the converter and RH degassing. Even the application for scrap characterization needs to be robust to environmental influences, like weather or light

conditions. For image analysis applications, either the observation method is chosen for the environment, or the environment is adapted to allow for a certain observation method. Usually both aspects are optimized as far as possible.



(a) (b) (c)

Figure 2 – (a) Installation of measurement system for scrap characterization and envisaged analysis of images, (b) Converter vessel and lining breakouts (image credit voestalpine Steel Division), (c) RH process scheme and camera surveillance at the top of the degassing vessel.

For scrap characterization, the demand was to provide fast and relatively cheap solutions for an efficient and thorough use in scrap management. For the visual recognition of scrap parts on the truck, a simple cost-effective optical camera with short data read-out times is used. The goal for the overall processing time for the analysis of the scrap load on the truck is at around two minutes per truck. To reach that goal, also considering the additional time necessary for the chemical analysis of components by LIBS, locally installed GPU-based solutions are being explored to improve processing speed. Small components, reflective surfaces, overlapping objects and edges present significant challenges for accurate segmentation. Illumination conditions play a crucial role here, as shadows or reflections can often be detected as separate segments. Therefore, the installation will be done in a way to minimize effects of weather (e.g., wet or dirty surfaces due to rain) and a uniform light source will be installed to establish constant lighting conditions for all situations.

For the converter and RH plant, the high temperatures are difficult to handle for surveillance equipment. In both cases, distance from the heat source (i.e., liquid metal melts) is a part of the solution. In the converter, measurements will be done during treatment pauses when the ambient heat is less strong, and the setup will be protected by housing from dust and damage. The laser beam [4] scans the inner walls of the vessel and can thus give a complete representation of the remaining wall thickness. The thermal imaging is done from the outside at some distance from the vessel and can be post-processed by mapping algorithms to obtain a 3D view of the temperature distribution across the vessel surface. In the RH vessel, the camera is installed in a water-cooled shaft flushed with nitrogen and protected by a view glass and is thus capable of operating during treatments, facing the liquid melt surface with temperatures of around 1600 °C for extended amounts of time. A conventional optical camera is used in combination with an infrared filter and automatic brightness adaptation to be able to capture the dynamics of the liquid metal melt. More crucial than adapting to high temperatures and brightness levels are sufficient camera resolution (of the order of 500 pixels per meter) and framerate (for single image evaluation of the order of 5 fps is enough, for flow analysis a minimum of 20 fps is required), considering the limited space available in the installation shaft.

Any protective glass or shielding of measurement setups need to be cleaned regularly, in order to guarantee an unobstructed view, although it is also possible to analyze imperfect images to a certain degree by removing or discarding such areas in a post-processing step. The automated detection of image quality to exclude sequences without informative value is another aspect in efficiently extracting information from image data.

Both applications of laser technology in the scrap characterization and converter vessel wear detection require safety considerations prior to the installation. The LIBS system for the chemical analysis of scrap is not an eye-safe laser, which makes appropriate shielding or security zones necessary. The LaCam system is an eye-safe class 1 laser, so no additional security is necessary.

DATA ANALYSIS METHODS

For the analysis of image data, many options – conventional as well as new – are available. Already before the advent of machine learning and AI methods, extracting information from image data was done using methods such as thresholding, contrast or feature detection, pre-processing of images using filters for smoothening or sharpening, or the detection of flow and motion by analyzing several images as a sequence [5] [6]. More recently, many machine learning (ML) based algorithms have been developed to extract patterns or features from images through high-dimensional fits e.g., with convolutional neural networks (CNNs) trained for object recognition [7] [8] [9] or clustering algorithms [10] [11], and also flow detection schemes are possible with such methods [12]. All image data processing requires some sort of identification of the region of interest – may that be the edges of a truck, the vessel opening or the melt surface in the vacuum chamber. The definition of the ROI is usually based on features of interest detected in the image [13], combined with manual input from the installation setup and geometrical boundary conditions.
In addition to the information extracted directly from the image, accompanying process data is usually necessary to correctly interpret or post-process the image information in the context of the physical processes that are depicted. This can either refer to time series data of relevant process quantities such as pressure, temperature, input or triggers by the operator, information on chemistry or physical state of the measurement object, or other information on boundary conditions. Table 1 contains an overview over the additional data that is necessary for each of the discussed cases.

Table 1 – Additional process data and information complementing the image data.

Accompanying measurement data to make sense of the images	
Scrap characterization	LIBS analysis of chemical composition, geometry of setup, weight of scrap load
Converter wear	Temperature measurements, strain measurements, vessel age, process data
RH degassing	Process data on pressure, offgas composition, treatment type, alloying additions

Scrap characterization

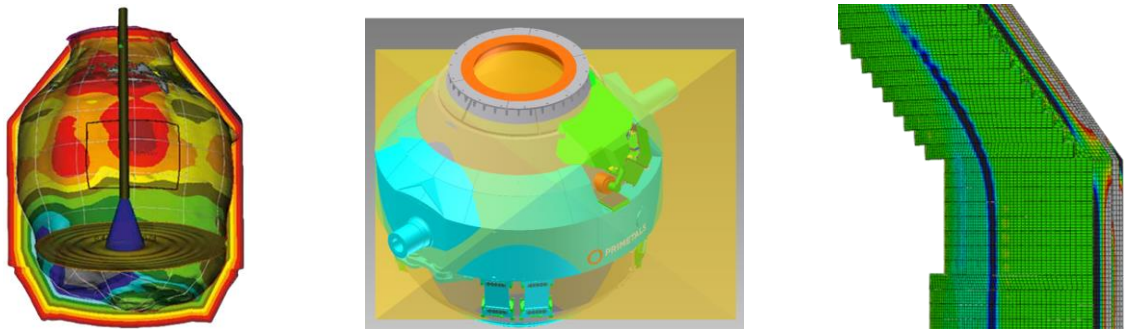
The image data serves to detect different pieces of scrap, to be able to determine their dimensions and thus calculate the volume contained in one truck load of scrap. The main challenge is to identify which surfaces belong to the same piece of metal. Figure 3 shows a comparison of the original image with the analysis obtained by image segmentation with a Segment Anything Model (SAM) [14]. This approach applies a segmentation of the image to recognize similar areas across the image. Subsequently, the identified segments are compared, similar or near-identical copies are eliminated, and the algorithm is applied again. Further refinement can be achieved by applying clustering algorithms to the identified segments. With this strategy already many objects can be detected successfully. While this algorithm performed comparatively well in comparison to others (e.g., region-based CNNs) that have been tested, it is clear that there are still some cases in which a single object cannot be detected as one connected piece. In particular, small components, reflective surfaces, and edges present significant challenges for accurate segmentation. Further refinement of models by additional data (e.g., average object size or numbers) and improved model training and re-application schemes (supported e.g., by clustering algorithms) is necessary to improve the outcome.
Furthermore, a mere segmentation of images does not bring any knowledge for the purpose as such but – most importantly – needs to be complemented by further data. The image analysis is supplemented by information on the geometry and dimensions of truck and measurement system, as well as scrap weight, to be able to estimate real sizes and estimate the scrap volume from a 2-dimensional surface analysis. Most importantly, to estimate the mean composition of metal on the truck, information on the chemical composition of the objects is necessary. To that end, the LIBS system is implemented and integrated into the detection system along the optical camera, providing information on the chemical composition of selected measurement points in the domain. The results of chemical composition measurements will be used to identify connected objects, thus improving the object detection by segmentation. Vice versa, information from the image segmentation could be used to determine at which coordinates the LIBS measurement should be done.

(a) (b) (c)

Figure 3 – (a) Unprocessed generic scrap image [15], (b) Image segmentation mask, (c) resulting segmented image.

Converter wear modelling

The LaCam system employed for converter lining wear measurement is able to provide an estimate of the vessel lining thickness based on laser triangulation measurements; an inbuilt temperature measurement by pyrometer can also provide a thermographic image of the inside lining temperature. For the laser scan, a pre-defined measurement path is executed via a measurement manipulator and based on the data a 3D image is reconstructed by the system. The laser evaluation can be done within a few minutes in different accuracies and resolutions and can provide an up-to-date estimate of the vessel lining after each treatment, to be made available to the operator. The IR camera provides more comprehensive data on the thermal distribution from the outside of the vessel. 2D data from the camera installed at a fixed point at a distance is mapped onto a 3D model of the vessel, using reference points installed at the vessel to calibrate and correctly map the data. An additional research question is the possible detection of increased temperature on the outer steel shell by thermal camera, indicating the presence of premature wear in the refractory lining, giving early warning of imminent break-out incidents. These images of wear and temperature status are already crucial pieces of information to increase plant safety and optimize process maintenance strategies. Beyond that, they can be used to validate and calibrate thermomechanical simulations of the lining state, developed to understand the phenomena leading to damage of the lining [16] [17], together with further measurements of temperature on the outer side of the vessel via thermocouples, measurements with strain gauges as well as data on the vessel age and processes. Moreover, material properties tested in lab setups can give complementary information on the wear behavior. All these data sources combined with simulations can give a comprehensive picture of the wear caused by the process and evaluate the current state of the vessel. Based on these data, maintenance measures can be scheduled with much higher precision thus optimizing resource use as well as costs.



(a) (b) (c)

Figure 4 – (a) LaCam example image (image credit at Minerals Technologies [4]), (b) thermal image mapped to 3D vessel geometry (image credit Primetals Technologies Austria), (c) example of thermomechanical simulation (image credit Montanuniversität Leoben, Chair of Ceramics).

RH degassing

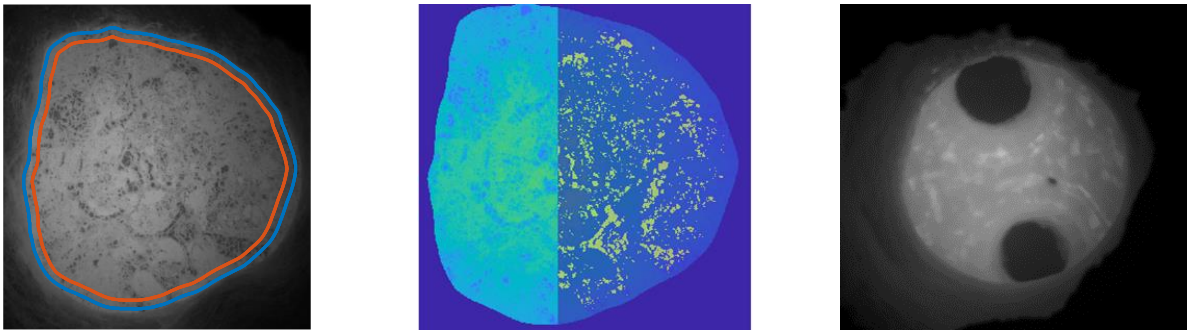
In this use case, images serve to estimate the process state at different instances of the process, both during and in between treatments. A relatively simple optical camera system for surveillance can provide a range of different data points on the state of the process and plant. During the process the dynamics and features of

the flow in the vacuum chamber are relevant to evaluate the efficiency of stirring and strength of reactions in the chamber. In between processes, the state of the vessel can be analyzed to give insights of flow geometry and maintenance needs. Both conventional and ML approaches have been tested. Figure 5 shows some examples of the images used in different analyses, previously published in [2] and [18].

For process state evaluation, as a first step a simple dynamic thresholding algorithm has been developed, identifying features within a ROI in the image of the melt surface inside the vacuum chamber [2], shown in Figure 5 (a) and (b). This approach has proved to be a fast and reliable method to determine the state of the process and strength of reactions, thus classifying the process dynamics and intensity. The methods, ranging from classical thresholding approaches to clustering algorithms such as k-means [11], are able to identify different patterns of flow behavior. The size, shape, and number of detected features in an image can, when related to information on the kind of treatment (degassing or decarbonization) or alloying events, discriminate a stable expected from an unstable unforeseen state of the process.

ML-based approaches have been developed and tested in order to detect or alleviate blurriness in images due to obstructions of view either by dirt on the view glass or by the injection of alloy materials to the chamber. One algorithm was applied to detect blurriness [19] using a CNN [20] developed for handwriting recognition [21]. Results showed a success rate of above 93% in recognizing blurry images and excluding them from further analysis. For the improvement of images, two dehazing algorithms have been tested [22] [23]. Unfortunately, neither algorithm was able to achieve substantial improvement, and partially led to unphysical or unrealistic outcomes. Additionally, the processing time of the algorithms per image is too long for a real-time application to video data analysis.

Methods for flow characterization such as particle image velocimetry (PIV) or optical flow [24] as well as the ML-based RAFT algorithm [25] have been tested, but video observations show that the melt surface is often not directly accessible due to the formation of argon gas bubbles and splashes impeding the view on the liquid melt flow. Moreover, again the ML-based approach turned out to be too slow for a real-time video analysis.



(a) (b) (c)

Figure 5 – (a) RH image with ROI, (b) RH image of bubble-dominated regime and detected features superimposed on right image half, (c) empty lower vessel in between treatments (all three images from [2]).

In-between treatments, camera images such as shown in Figure 5 (c) show the state of the vessel lining deteriorating over time. In particular, the wear in the snorkels is visible in the vacuum chamber. Together with data on the chamber geometry, image analysis can be done at fixed times after the end of a treatment with thresholding and edge detection algorithms to identify and measure certain geometrical features at known positions inside the chamber. From this, representative values of the current geometry (i.e., snorkel diameter) can be extracted, describing the changes in vessel geometry due to erosion in the up-snorkel. The information can be employed for vessel state evaluation or used in numerical models [26] for a more realistic simulation of flow conditions in a modified geometry.

DATA ACQUISITION AND STORAGE STRATEGIES

Image data is much more extensive in comparison to time series data of single measurement quantities. It is therefore necessary to consider what information to extract from the image detection setup, how and where to processes it and what is the relevant information to be conserved in the process monitoring and control systems. In most cases, it is neither feasible nor necessary to store large amounts of raw image data. In some

cases, image data might even only be used for the setup, validation and/or calibration of a model, provided by occasional measurement campaigns with an offline solution for data storage. For the final implementation in all three cases, the image data is extracted from the sensor, directly processed online, and only relevant image parameters are kept for long-term storage.
In the scrap detection case, the measurement setup of optical and LIBS sensors will be implemented as a soft sensor for the evaluation of metal composition on the truck, and only data on estimated chemistry and quantity will be stored, along with some relevant parameters evaluating the model performance and predictive quality. In the observation of RH degassing, images are acquired by the process control system, analyzed in connection with current process data, and then the image characterization parameters, i.e., flow characteristics or geometrical chamber features, are stored in the system in the form of a time series. In that way, the necessary storage capacities are rather small in comparison to the wealth of data obtained. Only in dedicated campaigns with increased framerate or resolution, raw image or spectroscopic data is conserved and could be used for the purpose of model development. For the case of converter wear, the image data's main purpose is two-fold. On the one hand, it serves for model validation and understanding of the wear process. For this purpose, the complete data is stored in dedicated measurement campaigns and used with complementary information from other data sources in the process in the validation of a finite element simulation of the material. On the other hand, continuous wear will be monitored over time to optimize the vessel use and maintenance strategy. In this case, information from all data sources is used together with modelling approaches to estimate the current wear of the vessel. Thus, the storage of raw data of laser, thermal or image sensors is in all three cases likely not necessary on longer time scales and does not require large data storage capacities.

CONCLUSIONS ON DATA ANALYSIS OUTCOMES AND PURPOSE IN INDUSTRIAL PROCESS

We have discussed different instances of image analysis to provide improvement and solutions for different problems in the metallurgical industries, highlighting how the same questions and aspects have to be considered in each application independently of the nature of the problem.
In one case, the described measurement setup effectively results in a soft sensor for efficient scrap characterization at the entrance of a plant to be used for an optimal feed mix design for further use in primary metallurgy. In two other cases, imaging sensors can provide an estimate of the state of a metallurgical vessel and help to estimate maintenance needs for a better use of resources and process stability. Moreover, surveillance has shown to yield benefits beyond process observations for safety of operation, and in one case the described analyses have allowed an automated evaluation of the process behavior in the vessel. Image data and the information extracted from them can also be used in connection to numerical modelling and simulations and serve for validation and calibration purposes.

ACKNOWLEDGMENTS

The authors gratefully acknowledge the funding support of K1-MET GmbH, whose research program is supported by COMET (Competence Center for Excellent Technologies), the Austrian program for competence centers. COMET is funded by the Austrian federal ministries for Innovation, Mobility, and Infrastructure and Digital and Economic Affairs, and the Provinces of Upper Austria, Tyrol, and Styria.
The DiGreeS project is funded by the European Union. Views and opinions expressed are however those of the author only and do not necessarily reflect those of the European Union or the European Health and Digital Executive Agency (HADEA). Neither the European Union nor HADEA can be held responsible for them.
The projects ECO2LIFE and OpTwinFlow have received funding from the Austrian FFG's program "Produktion und Material" under project numbers 50647011 (ECO2LIFE) and 45974027 (OpTwinFlow), respectively.
The INEVITABLE project has received funding from the European Union's Horizon 2020 research and innovation program under grant agreement No 869815. This paper reflects only the authors' views, and the European Commission is not responsible for any use that may be made of the information it contains.

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GLOBAL-LOCAL ORDER DRESSING: HOW STEEL PRODUCERS CAN USE PRODUCT CONFIGURATION AND RULE-BASED ENGINES TO GENERATE PRODUCTION ORDERS

Carlos Olmos, Heinz Zechner, Andrew Betzold, Sean Baker, Eric Meta, Jiri Blazek, Gagandeep Sehgal, Marc Schwarzer – PSI Software SE

Quality specifications are crucial for the metals industry to ensure consistent quality and safety. Integrating these specifications into the manufacturing execution system (MES) is essential for maintaining expected quality levels, minimizing errors, and enhancing efficiency, thereby meeting regulatory requirements and customer expectations. However, metals producers with geographically distributed locations face challenges in ensuring compliance with international quality standards, such as inconsistent data representation across different systems and varying completeness levels. Addressing these challenges requires a robust strategy that includes effective communication, standardized processes, and advanced technology integration. This paper details how Global-Local Order Dressing serves as a central knowledge base for the steel industry, enabling producers to leverage a unified quality repository with local download capabilities. As part of the digital transformation journey which is required for process optimization, the solution provides instant access to centralized industry specifications, reducing time-consuming and error-prone data entry at each local instance, allowing quality assurance teams to focus on core tasks and enhance productivity. We will further show how regardless of the location, the solution ensures that all teams adhere to the same best practices, resulting in consistent and high-quality outputs.

KEYWORDS: ORDER DRESSING; QUALITY; GLOBAL; LOCAL; EFFICIENCY; KNOWLEDGE; GOVERNANCE; IAI;

INTRODUCTION: THE ORDER DRESSING DIRECTIVE IN MODERN METALS PRODUCTION

In the metals industry, the transformation of commercial sales orders into detailed manufacturing instructions—commonly known as Order Dressing—is an indispensable yet traditionally manual and error-prone process.

This task demands the reconciliation of several complex dimensions:

- **Quality Specifications**: Encompassing chemical, mechanical, and dimensional requirements derived from international and customer-specific standards.
- **Manufacturing Rules**: Including process sequences, setup parameters, equipment capabilities, and energy/material inputs.
- **Multi-Site Variability**: Different plants often have unique configurations, legacy practices, and locally interpreted standards.

The traditional approach relies heavily on fixed catalogs and spreadsheets that require manual cross-referencing and expert intervention. This creates bottlenecks in engineering offices, introduces variability into production, and limits scalability. Yet the ultimate challenge lies in balancing global standardization with local adaptability—ensuring consistency without undermining site-specific operational realities.

The Global-Local Order Dressing platform from offers a modern alternative that simplifies the rigid legacy systems by providing a centralized, rule-driven knowledge base with download capabilities and an inference engine that automates technical elaboration to generate production orders with comprehensive quality and manufacturing details. This paper will explain the details of this dual Global-Local platform for end users.

KNOWLEDGE-BASED ORDER DRESSING ARCHITECTURE

At the heart of the platform is a multi-layered knowledge base encoding expert industrial know-how. This digital foundation is structured into three interdependent models, including Quality Data Model, Manufacturing Data Model, and Governance Model:

Quality Data Model

- Encodes normative standards (e.g., ASTM, EN, ISO, API), customer-specific specifications, and internal criteria –a.k.a internal qualities.
- Defines required tests (e.g., tensile, hardness, charpy, ultrasonic), sampling instructions, and acceptance limits.
- Captures relationships between product attributes (e.g., yield strength vs. heat treatment, melt grade chemistry and properties vs heat treatment practices).

Manufacturing Data Model

- Formalizes process routes (e.g., Rolling → Pickling → Finishing → Inspection → Shipping).
- Contains algorithmic formulations for material usage and transformation per process step.
- Embeds equipment-level parameters, such as rolling speeds, furnace cycles, or coating compositions.

Governance Model

- Allocates domain responsibility across engineering functions:
- Quality engineers maintain test logic.
- Process engineers govern routing and setup rules.
- Supply chain manages labeling, packaging and shipping instructions.
- Ensures traceable cross-domain dependencies (e.g., chemical tolerances affecting downstream cooling rates).

Technical Elaboration

The rule engine automates the technical elaboration through a sequenced six-step process:

1. **Commercial Setup**: Gets customer order attributes (e.g., material type: seamless stainless steel tube, diameter: 50 mm, specifications (e.g. EN 10216-5, ASTM A312).
2. **Quality Data Model**: Resolves all applicable standards, identifies necessary inspections, and derives tolerance ranges.
3. **Route Composition**: Assembles the required process flow from applicable operations, filtered by site capabilities and production constraints.
4. **Material Transformation and Demand Calculation**: Computes input materials and dimensions (e.g., billet weight for a target tube length).
5. **Setup Parameter Generation**: Translates high-level routing into executable machine instructions (e.g., annealing at 950°C ±10°C, line speed 3.5 m/s).
6. **Costing and Standardization**: Assigns cycle times and estimated cost per process, enabling close colaboration and integration with ERP and MES systems.

Production Order Details

The final output is a comprehensive, executable production order including:

- Inspection protocols with sampling frequencies and sample specifications.
- Line-specific machine instructions.
- Documented compliance against governing standards (EN, ISO, API, ASTM).
- Embedded digital traceability for audit purposes (versioning, change logs).

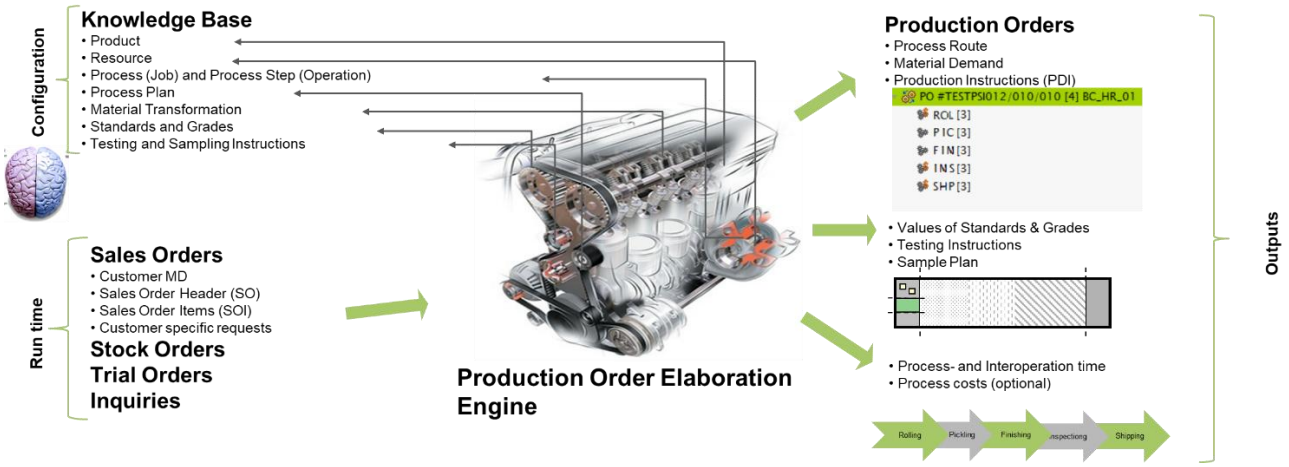


Fig.1 – Knowledge Based Order Dressing Architecture

MULTI-SITE COMPLEXITY: THE CHALLENGE OF FRAGMENTED QUALITY AND PROCESSES

Multi-plant operations, though offering flexibility and proximity to markets, present significant operational and governance challenges.

Quality Inconsistencies

- Variations in standard interpretation (e.g., one plant allows 0.30% max carbon for heat chemistry, another restricts it to 0.25%).
- Divergent test procedures and acceptance thresholds.
- Inconsistent documentation and traceability practices.

Process Heterogeneity

- Rolling mills with different capabilities require customized leadtime schedules.
- Differing heat-treatment cycles due to furnace limitations or historical practices.
- Varying material handling and logistics configurations.

Organizational Silos

- Local engineers with different backgrounds and expertise levels maintaining isolated rule sets.
- Redundancy in rule creation and difficulty aligning updates across plants.
- Limited knowledge transfer between facilities.

These inconsistencies lead to:

- Customer dissatisfaction due to variability in product performance
- Operational waste from rework and scrap.
- Exposure to compliance risk under ISO, API, or local regulations.
- Inefficient resource utilization and extended lead times.

GLOBAL-LOCAL ORDER DRESSING PLATFORM: GOVERNANCE WITH FLEXIBILITY

Addressing these challenges requires a robust strategy that includes effective communication, standardized processes, and advanced technology integration. Our Global-Local Order Dressing serves as a central knowledge base for the steel industry, enabling producers to leverage a unified quality repository with local download capabilities. As part of the digital transformation journey, which is required for process optimization, the solution provides instant access to centralized industry specifications, reducing time-consuming and error-prone data entry at each local instance, allowing quality assurance teams to focus on core tasks and enhance productivity.

Dual Repository Architecture

The platform enforces standardization through a two-tiered repository model:

- Global Repository
  - Central hub maintained by corporate teams.
  - Contains core standards, tests, and production rules.

- Local Repositories
  - Plant-specific overlays mapped to the global layer.
  - Allow for operational customization (e.g., plant-specific test adaptations, specific tolerances).

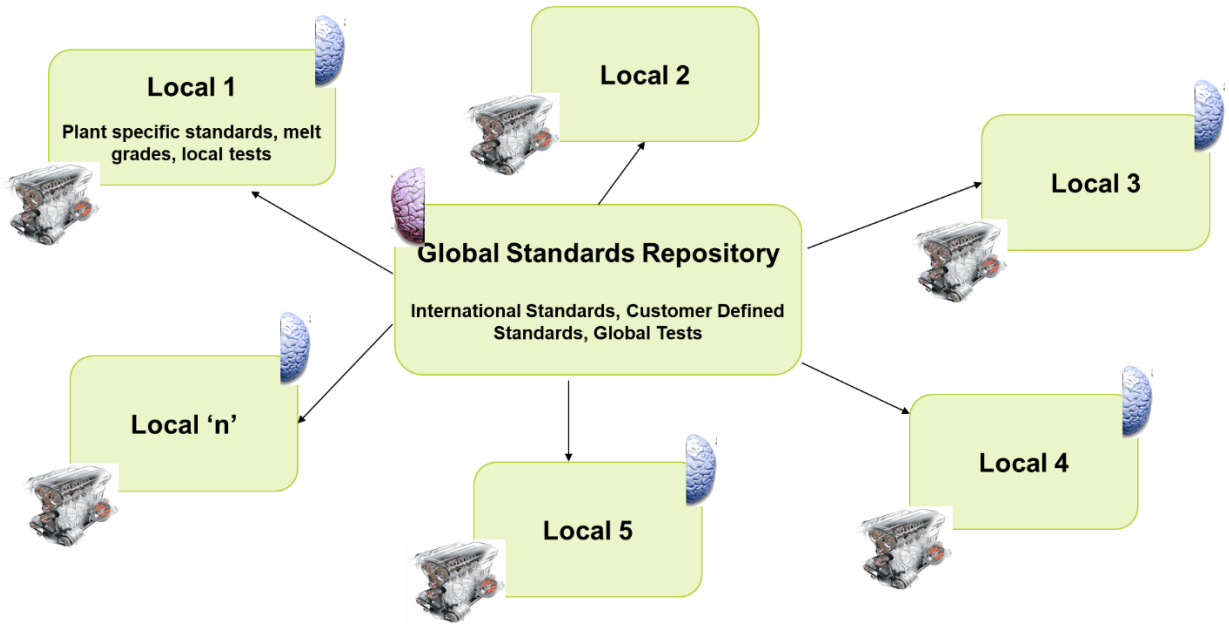


Fig.2 – Global-Local Order Dressing – Dual Repository

Governance and Role Responsibilities

- Global Role (Corporate Engineering)
  - Maintains master standards (ASTM, ISO, etc.).
  - Assigns applicable rules to plants through a controlled release mechanism.

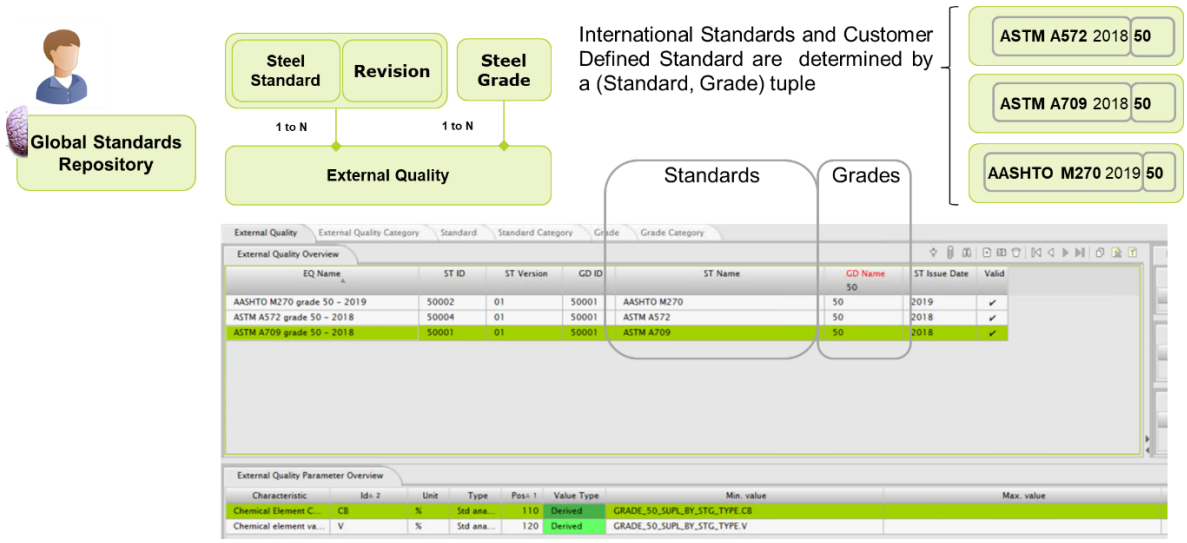


Fig.3 – Global-Local Order Dressing – Global Repository

- Local Role (Plant Engineering)
  - Maps global rules to site-specific entities (e.g., API 5L X70 specification is mapped to melt grade ‘ABC123’ at plant ‘A’ whereas the same specification is mapped to melt grade ‘XYZ987’ at the plant ‘B’).
  - Creates extensions only where allowed (e.g., local inspection procedures).
  - Operates under restricted permissions—cannot modify core global rules.

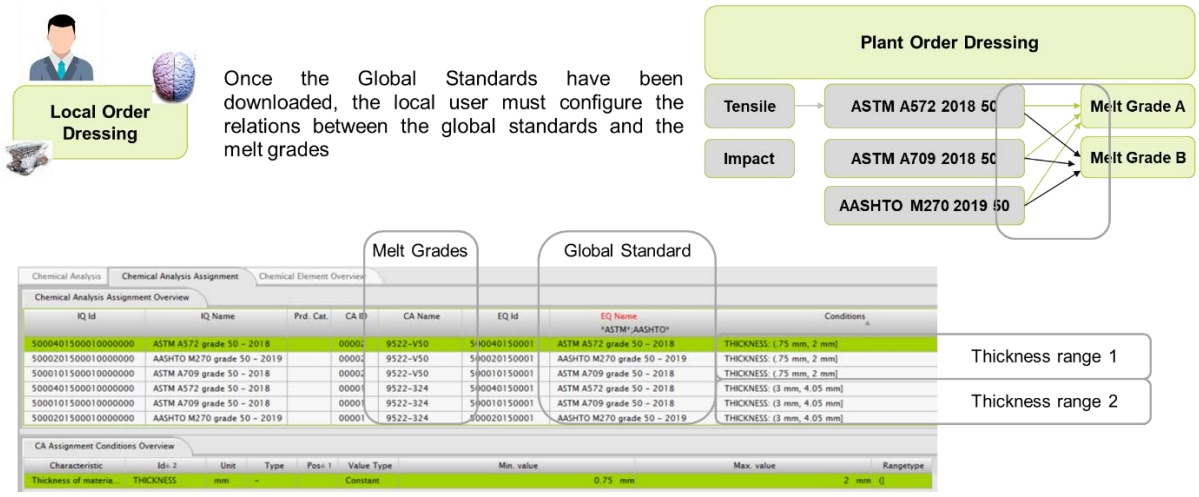
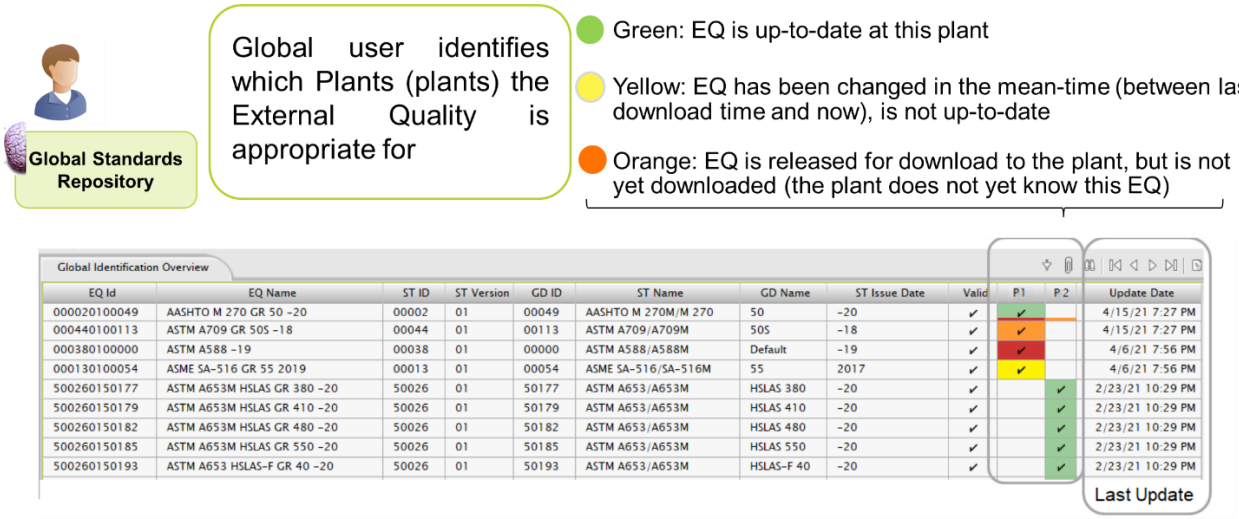


Fig.4 – Global-Local Order Dressing – Local Repository

Conflict Mitigation and Harmonization

- Baseline Enforcement
  - Global rules enforce the minimum required compliance (e.g., minimum elongation for tensile tests).
- Permitted Extensions
  - Local engineers can add constraints (e.g., smaller coil weight for overhead crane limits).
- Synchronization Engine
  - Periodically syncs updates.
  - Blocks conflicting overrides.

- Tracks deviations and flags for audit or escalation.
- Monitors synchronization status:
  - Green = Up to date.
  - Yellow = Updates available, ready for download.
  - Orange = Global update released, local implementation lagging.



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000440100113	ASTM A709 GR 50S -18	00044	01	00113	ASTM A709/A709M	50S	-18	✔	✔		4/15/21 7:27 PM
000380100000	ASTM A588 -19	00038	01	00000	ASTM A588/A588M	Default	-19	✔	✔		4/6/21 7:56 PM
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Fig.5 – Global-Local Order Dressing Platform – Conflict Mitigation and Harmonization

OUTSTANDING BENEFITS

The global-local platform delivers measurable efficiency gains by automating error-prone manual tasks, reducing order-dressing time from weeks to hours and cutting data-entry mistakes. Quality consistency improves as all plants enforce identical international standards (e.g., ASTM, EN), while local adaptations for site-specific constraints (e.g., furnace capabilities) maintain operational flexibility. This harmonization directly reduces quality-related scrap, frees engineering bandwidth for innovation, and ensures audit-ready compliance across sites—turning standardization into tangible cost savings and competitive advantage.

It is also the starting point for a successful implementation of the so-called ‘Digital Twin’ and the creation of the first steps integrating Industrial Artificial Intelligence (IAI) models based on the usage of existing knowledge in its digital format.

After three successful implementations of this innovative digital platform, here is a list of outstanding benefits confirmed by our customers:

Error Elimination

- Reduces manual data entry errors by 60–80%.
- Eliminates standard interpretation discrepancies.
- Automatic validation of order completeness and feasibility.

Cycle Time Compression

- Order dressing that once took 2 weeks can be completed in under 1-2 hours (sometimes it takes minutes).
- Reduced queue time in engineering departments.
- Faster response to customer inquiries and modifications.

Resource Optimization

- Enables quality and engineering focus on process improvement and innovation.
- Reduces dependency on senior subject matter experts for routine tasks.

Standardization Achievements

- Uniform interpretation of EN, ASTM, and ISO across all sites.
- Consistent application of customer-specific requirements.
- Standardized documentation and reporting formats.

Audit Readiness

- Full traceability for internal and external inspections.
- Automated compliance verification against multiple standards (multi-quality requests).
- Reduced audit preparation time.

Non-Conformance Reduction

- Outdated rule usage is automatically prevented.
- Real-time validation of production parameters.
- Proactive identification of potential quality issues.

Market Responsiveness

- Rapid deployment of new product specifications across global sites.
- Faster time-to-market for new product variants.
- Enhanced ability to respond to regulatory changes.

Scalability Benefits

- Onboarding new plants with consistent rule application in 2-3 months instead of years.
- Reduced training requirements for new engineering staff.
- Standardized processes enable easier technology transfer.

Cost Control

- Scrap and rework costs reduced through consistent production logic.
- Reduced engineering overhead through automation.
- Improved yield through optimized process parameters.

The transformation from fragmented, manual processes to unified, intelligent systems is not merely a technological upgrade—it represents a fundamental shift in how manufacturing knowledge is captured, shared, and applied across global operations. The future belongs to organizations that can effectively harness their collective expertise through intelligent platforms that enable both global consistency and local adaptability.

IMPLEMENTATION AND DEPLOYMENT STRATEGY

Deployment begins by migrating core standards and process rules into the global repository, curated by corporate experts. Plants are subscribed to the global repository and then create their concrete instance by linking the global standards (e.g., API 5L) to local melt grades and adding site-specific parameters (e.g., max coil weight, sample taking details). A sequence of recommended actions for a successful deployment strategy are:

- Data consolidation and Harmonization
- Pilot implementation
- Multi-site rollout
- Optimization and Continuous improvement

Governance is critical: corporate controls global objects, plants own local extensions, and automated sync alerts (Green/Yellow/Orange statuses) enforce update discipline. Bi-weekly global releases and compliance audits sustain the system, transforming fragmented sites into a synchronized production network within 6-9 months.

Finally yet importantly, Change Management is key for a successful implementation of the digital platform, since it requires discipline through visibility and accountability from top management and core business areas (Quality, Engineering, Processes, and Supply Chain) ensuring organizational and technical readiness, subject matter experts involvement, comprehensive training and user adoption.

CONCLUSION

The global metals industry stands at a critical juncture where traditional approaches to order processing and quality management are no longer sufficient to meet the demands of modern manufacturing. The Global-Local Order Dressing platform represents a paradigm shift from reactive, manual processes to proactive, intelligent systems that leverage decades of accumulated expertise.

Key Strategic Advantages:

- Operational Excellence: Dramatic reduction in processing time and error rates while improving resource utilization
- Quality Assurance: Consistent application of standards and requirements across global operations
- Regulatory Compliance: Automated validation and documentation for audit readiness
- Strategic Agility: Rapid response to market changes and new product requirements
- Scalable Growth: Framework for efficient expansion and knowledge transfer

Implementation Success Factors:

- Strong executive sponsorship and clear strategic vision
- Comprehensive change management and user adoption strategies
- Phased deployment with pilot validation and continuous improvement
- Integration with existing systems and processes
- Long-term commitment to platform evolution and optimization

The companies that successfully implement manufacturing intelligence platforms will establish sustainable competitive advantages in efficiency, quality, and time-to-market responsiveness. Those that continue to rely on traditional approaches will find themselves increasingly disadvantaged in a rapidly evolving global marketplace.

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Towards zero-defect manufacturing for flat steel production - Introduction of the SurfConInspect Project

J. Brandenburger – VDEh-Betriebsforschungsinstitut, Germany
C. Schirm – Thyssenkrupp Rasselstein GmbH, Germany
N. Matskanis – Centre d'Excellence en Technologies de l'Information et de la Communication, Belgium
M. Vannucci – Scuola Superiore di Studi Universitari e di Perfezionamento Sant'anna, Italy
M. Krätzner – Salzgitter Flachstahl GmbH, Germany
L. Dorel – Clecim France SAS, France
E. Borasio – weAR S.r.l, Italy
P. Argoneto – yourscienceEDU s.r.l., Italy

Resource efficiency and competitiveness are the main objectives of the European Green Deal. In this global restructuring process, improving yield and reducing waste with the aim of zero-defect production are cost-effective ways for European steel manufacturers to realise more sustainable production.
Enabling zero-defect manufacturing for flat steel production requires an early detection of surface defects and a fast and adequate control action once a defect appears. Consequently, the RFCS research project SurfConInspect follows a holistic approach incorporating new concepts for the measuring of surface defects as well as for the support of adequate control actions.

KEYWORDS: ZERO-DEFECT MANUFACTURING – PRODUCTION CONTROL– FLAT STEEL – DIGITALISATION – SURFACE INSPECTION – AUGMENTED REALITY – ARTIFICIAL INTELLIGENCE

The aim of the SurfConInspect project is to enable zero-defect manufacturing in flat steel production by implementing a new level of surface quality control. Therefore, the SCI project follows a holistic approach incorporating new concepts as well for the measuring of surface defects as for the support of adequate control actions. Qualified by optimized robust detectors and advanced pre-trained classifiers a distributed SCI framework will be implemented providing robust and reliable control actions based on quality information of highest precision.

The SCI framework will exploit the latest innovations in the field of Augmented Reality (AR) devices to realize a flexible user-friendly human machine interface.

The applicability of this system will be demonstrated in five industrial use-cases at tin-plate and automotive production where the demands on surface quality are highest:

- Implementation of automated cutting control for heavy defects at a pickling line (PL) of tin-plate production to prevent strip breakages at subsequent processes.
- Optimized control of the process speed at the pickling line based on the scale affection of the individual coil.
- Improved quality control at tinning lines (TL) through the realization of online grading based on various surface defect types and generation of optimized in-coil control actions
- Improved quality control at galvanizing lines (EGL) through the realization of online grading based on various surface defect types and generation of optimized in-coil control actions
- Exploit the latest innovations in the field of Augmented Reality (AR) devices to realize a flexible user-friendly human machine interface for the improvement of the recoiling line process.

All these objectives will be verified as demonstrators implemented at the two industrial partners thyssenkrupp Rasselstein and Salzgitter Flachstahl.

Automation on thermal control of blast furnace

Ryosuke Masuda – JFE Steel Corporation, Japan
Yoshinari Hashimoto – JFE Steel Corporation, Japan

Accurate process control through automation is the key to achieving efficient and stable operation of a blast furnace. In this study, we developed an automatic control system of hot metal temperature (HMT). To cope with the slow and complex process dynamics of the blast furnace, we constructed a control algorithm that predicts eight-hour-ahead HMT using a two-dimensional (2D) transient model and calculates optimal target pulverized coal ratio (PCR) and pulverized coal flow rate by non-linear model predictive control (NMPC). An evaluation in a real plant showed that the developed control system suppressed the effects of disturbances, such as the changes in the coke rate and blast volume, and successfully reduced the average control error of HMT by 4.6 °C compared to the conventional manual operation. The developed control system has contributed to the reduction of reducing agent rate (RAR) and CO_2 emissions.

KEYWORDS: BLAST FURNACE – HOT METAL TEMPERATURE – MODEL PREDICTIVE CONTROL – PROCESS CONTROL – REDUCING AGENT RATE

INTRODUCTION

In the blast furnace process, it is crucial to maintain hot metal temperature (HMT) close to its target value. When the temperature of hot metal and slag decreases, the viscosity of the slag increases, making it difficult to discharge hot metal from the bottom of the furnace, thus decreasing the productivity of the blast furnace. Conversely, an excessively high HMT also leads to an excess consumption of the reducing agents. Reducing the variation in HMT makes it possible to keep the HMT near the lower bound, thereby reducing RAR.

Due to the large heat capacity of the blast furnace process, the immediate effect of the control actions such as the manipulation of the pulverized coal ratio is weak, and it is difficult to control HMT. Therefore, it is necessary to calculate appropriate control actions based on future predictions to control HMT accurately. A number of methods have been proposed for controlling HMT. Agrawal et al. developed a proactive thermal indicator based on the energy balance for controlling HMT [1]. Azadi et al. conducted a simulation study to control the thermal status using a hybrid dynamic model [2]. We developed a two-dimensional (2D) transient model of the blast furnace [3] and achieved the accurate prediction of the eight-hour-ahead HMT by embedding moving horizon estimation (MHE) [4]. We also implemented an operation guidance system to control HMT by non-linear model predictive control (NMPC) in real plants [5]. However, these conventional technologies are all limited to be used in operation guidance systems, which present the recommended control actions to human operators. In this study, we developed a control system to realize the full automation of HMT control and verified its control performance in an actual plant [6, 7].

The selection of appropriate manipulated variables is an issue for controlling HMT. The HMT can be controlled by manipulating the pulverized coal ratio (PCR), which is the amount of pulverized coal per ton of hot metal, the blast moisture (BM), and the blast temperature (BT). There are practical restrictions on most of these manipulated variables, however. The BM should be kept near the lower limit since the addition of moisture requires an excess amount of reducing agent to compensate for heat absorption by the decomposition of water vapor. In recent years, the BT has been kept at the upper limit in an attempt to reduce RAR. Since BM and BT are less suitable for use as manipulated variables, PCR was selected as the manipulated variable in the developed control system.

In this study, a cascade control algorithm was constructed as shown in Fig. 1, comprising an outer HMT control loop and an inner PCR tracking control loop. The HMT controller calculates the target PCR based on the future

prediction of HMT, and the PCR tracking controller calculates the pulverized coal (PC) flow rate to match the target PCR and actual PCR. We also developed a closed-loop control system that automatically executes the control actions of the target PCR and PC flow rate. We finally evaluated the control accuracy of HMT in the real plant.

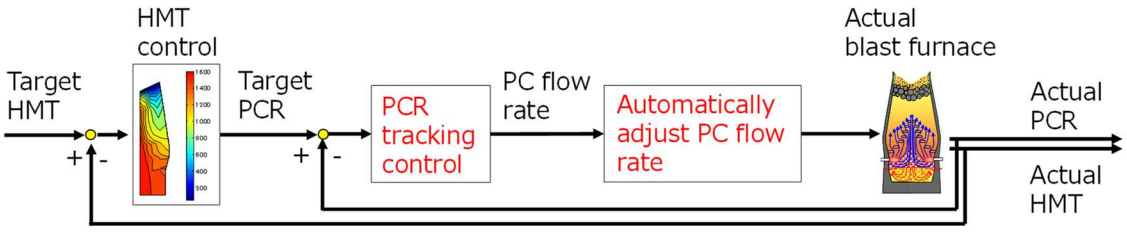

Fig. 1. Outline of automatic hot metal temperature control system.

MODEL PREDICTIVE CONTROL

In this study, HMT is calculated using a two-dimensional (2D) transient model that reproduces the layered structure of raw materials in the blast furnace [5]. This 2D transient model consists of four sub-models: gas flow model, solid flow model, mass balance model, and energy balance model. It calculates the state variables, including the temperature distributions of coke, iron, and gas every 15 minutes.

The NMPC algorithm operates as follows. First, the free response of HMT $y_{\mathrm{f}}(t_0+k)$ at current time step $t=t_0$ is predicted under the assumption that the input variables remain constant at the current values in the future. To predict up to 10 hours ahead, k takes the values from 0 to 40. The step response of HMT when PCR is increased by a unit amount $S_{\mathrm{PCR}}(k|t_0)$ is then calculated. Finally, the optimal operation amount of the target PCR (ΔPCR) to maintain the HMT near the set point is calculated based on Eq. (1).

$$\Delta PCR = -\alpha(\max(y_{\mathrm{f}}(t_0+k_1)-T_{\mathrm{U}},0)+\min(y_{\mathrm{f}}(t_0+k_1)-T_{\mathrm{L}},0))/S_{\mathrm{PCR}}(k_1|t_0) \quad (1)$$

where α is a relaxation coefficient. T_{U} and T_{L} are the upper and lower limits of HMT. With this control law, ΔPCR becomes zero while the predicted HMT is within the target range, i.e., between T_{U} and T_{L}. This is consistent with the operator's sense of operation that the minimum necessary control actions should be taken. The target PCR is then updated by adding ΔPCR to the current target PCR. According to the calculation of the step response in the previous work [3], the effect of PCR manipulation fully appears after about eight hours. Thus, k_1 was set to 32 in this study.

To achieve the target PCR determined by HMT control, the PC flow rate must be adjusted so that the actual PCR defined by Eq. (2) matches the target PCR.

$$PCR[\mathrm{kg/t}] = \frac{PCI\ [\mathrm{kg/min}]}{Prod\ [\mathrm{t/min}]} \quad (2)$$

The production rate (Prod) is almost proportional to the total oxygen flow rate, i.e., V_{O_2}, which is blown into the furnace. Hence, the control law is switched according to the change of V_{O_2}. If the change in V_{O_2} is large, feed forward control using the predicted PCR based on the predicted Prod by the 2D transient model is used. Otherwise, feedback control using the actual PCR derived from the actual Prod is used.

EVALUATION IN ACTUAL OPERATION

An automatic control system based on the control algorithm was implemented at an actual blast furnace. Fig. 2 shows the operational trend for 100 hours. The left column of Fig. 2 represents the operation in the blast furnace process, and the right column represents the operation result. The manipulated variables controlled by the developed system are the target PCR and the PC flow rate, as shown in Figs. 2 (b) and (c). Other variables (CR, BV, and EO) were manually manipulated by the operators, based on production rate and gas permeability (GP), as shown in Figs. 2 (g) and (h). In Figs. 2 (b), (f), (g), and (h), the red line represents the target value (or upper bound), while the blue line shows the actual value. The vertical axes in the left column are mean-centered, whereas those in the right column represent deviations from the target value (or upper bound) at time zero.

Despite the significant changes in CR, BV, and EO, HMT remained within the target range of ±20 °C as shown in Fig. 2 (f), due to appropriate adjustments of the target PCR and PC flow rate by the developed control system. For instance, the target PCR was increased by 10 kg/t at around 20 h to counteract the decline in HMT due to the decrease of CR at 12 h. In addition, the target and actual PCR were aligned by dynamically adjusting the PC flow rate in response to variations in Prod, which were induced by operators' manipulations in BV and EO from 15 h to 50 h.

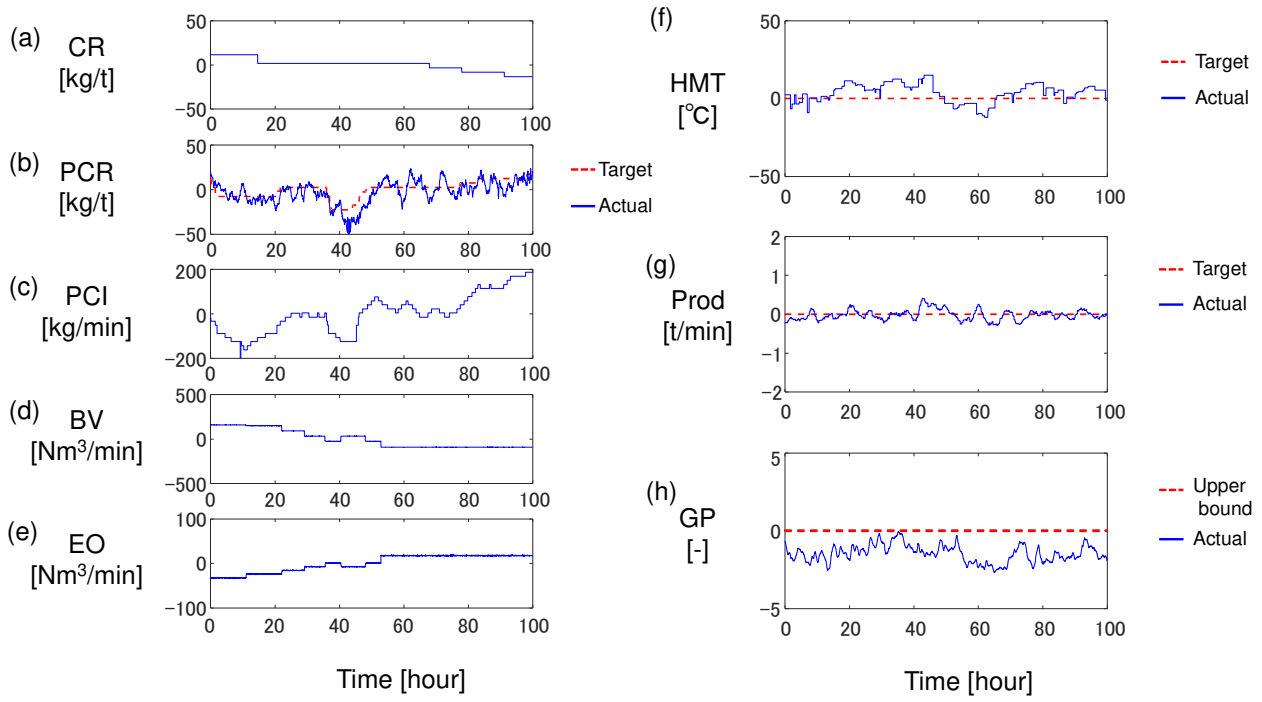

Fig. 2. Real operation result by developed control system.

Fig. 3 shows a histogram of the deviation of HMT from its target before and after the introduction of the developed control system. Conventionally, the operators controlled HMT to a value higher than the target value to avoid operational risks due to an excessively low HMT, and consumption of excess reducing agent was an issue. The developed control system successfully reduced the root mean square (RMS) of the control error by 3.4 °C, and decreased the average control error by 4.6 °C without increasing the frequency of excessively low HMT, i.e., less than -30 °C. This reduction in average control error has contributed to lowering the RAR and CO_2 emissions.

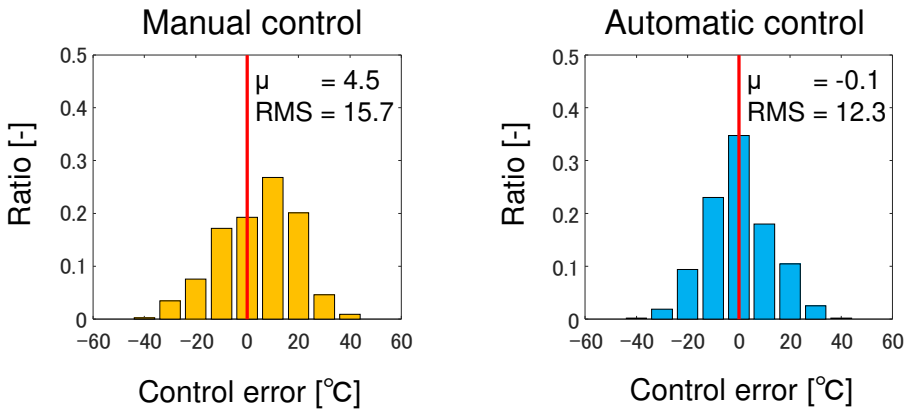

Fig. 3. Real operation result by developed control system.

CONCLUSION

In this paper, an automatic control system using nonlinear model predictive control (NMPC) was developed to control hot metal temperature (HMT). The automatic control system was implemented in an actual plant. As a result, the developed control system suppressed the effects of disturbances of changes in the coke rate (CR) and blast volume (BV) and successfully reduced the average control error of HMT by 4.6 °C compared to the conventional manual operation. The developed control system has contributed to the reduction of RAR and CO_2 emissions.

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SHP SYSTEM FOR SMART MONITORING AND OPTIMIZATION OF DCC DIGITAL BURNERS

Simone Zunino, Mariano Longo, Marco Daneri, Massimiliano Fantuzzi – Danieli Centro Combustion, Italy

The digital transformation of steel plants is essential to improve efficiency, product quality, and sustainability. A key enabler is the use of autonomous systems for real-time monitoring and optimization. Traditional furnace controls often lack continuous, detailed data and rely on manual checks, leading to inefficiencies and delayed maintenance.

To address this, Danieli Centro Combustion developed the Smart Heat Process (SHP) system – "Shape" – a platform for data acquisition and analysis in reheating and heat treatment furnaces. SHP builds a digital twin of the furnace, including burners and key components, enabling continuous monitoring of parameters such as pressure, temperature, flame behaviour, and vibrations. This supports optimal operation, improved combustion, and predictive maintenance.

Smart sensors installed on furnace components perform onboard data processing. Data are transmitted via long-range wireless links to gateways, then routed through the plant LAN to a local microserver. This server hosts a web interface for real-time and historical data visualization. Local storage ensures data ownership and reduces network load.

By autonomously collecting and processing high-resolution data, SHP enhances transparency and provides actionable insights for process optimization. Industrial trials confirm its ability to monitor key variables, calculate flow rates, and assess combustion efficiency and component health.

KEYWORDS:
SHP, SMART MONITORING, DIGITAL BURNERS, THERMAL PROCESSES, PREDICTIVE MAINTENANCE, DIGITAL TWIN

INTRODUCTION

In modern industrial operations, the drive for greater energy efficiency, reduced environmental impact, and improved process control has accelerated the adoption of advanced monitoring and optimization technologies. Among these, thermal processes – particularly those involving reheating and heat treatment furnaces – represent a critical area where innovation can deliver substantial operational and environmental benefits.

The Smart Heat Process (SHP) system – namely "Shape" – developed by Danieli Centro Combustion, is a state-of-the-art solution designed for the intelligent, autonomous monitoring and optimization of DCC digital burners. These burners are widely used in high-temperature industrial applications, where precise control of combustion parameters is essential to ensure product quality, energy efficiency, and compliance with environmental regulations.

Conventional burner systems typically operate with limited feedback, relying on zone-level data and indirect indicators. This lack of granularity can mask localized inefficiencies or malfunctions, such as imbalanced air-fuel ratios, flow restrictions, or uneven temperature distributions. The SHP system addresses these limitations by integrating a network of smart sensors and edge computing capabilities directly at the burner level, enabling the creation of a real-time digital twin of the combustion process.

This article provides a comprehensive overview of the SHP system, detailing its modular architecture, embedded smart sensor technology, and data acquisition and processing strategies. It also examines the system's communication infrastructure, which leverages long-range wireless protocols and local microserver storage to ensure robust, secure data handling. Additionally, the user interface is discussed, highlighting its capabilities for real-time visualization, historical data analysis, and actionable insights.

Finally, a real-world industrial case study is included to demonstrate the practical benefits of SHP, showcasing improvements in process stability, predictive maintenance, and emissions monitoring, concluding the discussion analyzing system's advantages and potential impact on the future of thermal process.

1. SHP MAIN FEATURES

The Smart Heat Process (SHP) system introduces a transformative approach to burner-level monitoring and control in industrial thermal processes. Its capabilities result from the integration of advanced sensor technology, embedded computing, wireless communication, and user-centered software design.
A core feature of SHP is its distributed intelligence, achieved through smart sensors equipped with onboard microprocessors. These sensors perform local data processing – including filtering, compression, and preliminary diagnostics – reducing the load on central systems and minimizing network traffic.
Another key capability is the real-time digital twin. By continuously acquiring and analyzing data across thermal, mechanical, and chemical domains, SHP constructs a dynamic virtual model of each burner. This enables continuous performance monitoring, real-time anomaly detection, and allows predictive maintenance.
SHP also features adaptive data acquisition, allowing sensors to adjust sampling frequency and resolution based on the operational regime. For instance, during transient phases such as ignition or shutdown, the system increases data granularity to capture critical events, while optimizing for efficiency during steady-state operation.
From a communication perspective, SHP employs long-range, low-power wireless protocols (e.g., LoRa) to ensure reliable data transmission across large industrial sites with minimal infrastructure. This is supported by a low-impact network architecture, using a limited number of gateways and a single microserver to manage and aggregate data.
A notable advantage of SHP is its local data sovereignty. All data are stored and processed within the plant's infrastructure, eliminating the need for cloud services and ensuring full control over sensitive operational information – an important factor in industries with strict confidentiality and compliance requirements.
Finally, SHP is designed to be modular and scalable, enabling incremental deployment – from a single burner to an entire furnace – without disrupting existing automation systems. This flexibility makes it ideal for both new installations and retrofitting legacy equipment.
Together, these features position SHP as a comprehensive, future-ready platform for intelligent combustion management in energy-intensive industries.

2. SYSTEM ARCHITECTURE

The architecture of the Smart Heat Process (SHP) system – see Fig. 1 - is engineered for robustness, modularity, and scalability, making it suitable for a wide range of industrial thermal applications. At its core, SHP is designed to overcome the limitations of traditional burner-level monitoring by enabling high-resolution, real-time data acquisition and analysis directly at the combustion source.

The system comprises four primary subsystems:

1. Smart sensor modules
2. Edge-level data processing units
3. Long-range wireless communication infrastructure
4. Centralized microserver with a web-based user interface

Smart sensor modules are installed directly on each DCC digital burner. These modules feature multi-parameter sensing capabilities – including pressure, temperature, vibration and molecule concentration. Unlike conventional sensors, SHP modules include embedded microcontrollers that perform local data pre-processing, filtering, and compression. This edge computing approach reduces data volume while preserving critical information.

Data processing units are distributed throughout the system and aggregate sensor data for interpretation. These units apply adaptive sampling strategies based on the operational regime (steady-state or transient) and detect anomalies or deviations from expected combustion behavior. This supports early fault detection and enables predictive maintenance.

Communication modules use long-range, low-power wireless protocols – such as LoRa (Long Range) – to transmit data from sensor nodes to the central server. This architecture minimizes cabling requirements and minimizes the load on the plant's Ethernet infrastructure. Dedicated communication frequencies ensure signal integrity and avoid interference with other systems.

The heart of the system is a microserver, which serves as the central data repository and processing hub. It stores both real-time and historical data locally, eliminating the need for cloud-based storage and ensuring data sovereignty. The server hosts a web-based interface that provides operators and engineers with intuitive access to system metrics, key performance indicators (KPIs), and diagnostic tools.

This distributed yet integrated architecture enables SHP to deliver high-resolution insights into burner performance, facilitate real-time optimization, and support scalable deployment across complex industrial environments.

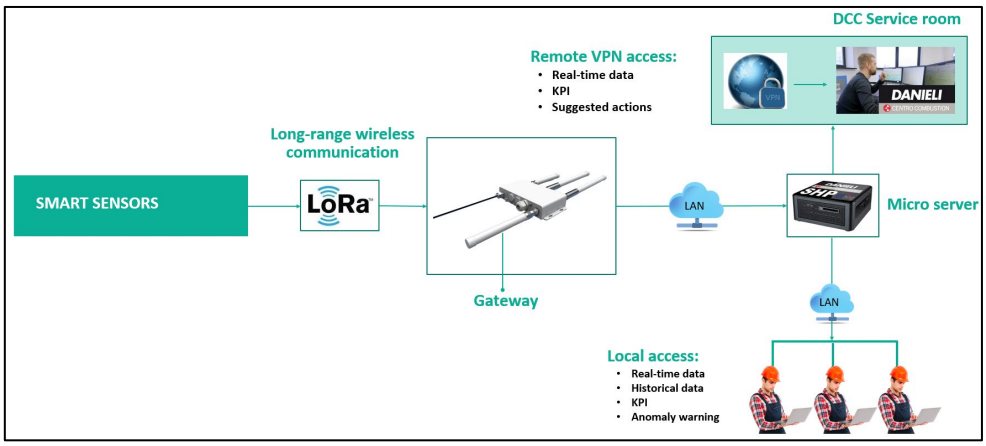

Fig. 1 – SHP System Architecture

3. SMART SENSORS AND DATA PROCESSING

The core of the SHP (Smart Heat Process) system is a network of advanced smart sensors - see Fig. 2 - purpose-built to operate reliably in the harsh and dynamic environment of industrial combustion systems. These sensors are not passive data collectors: they are intelligent modules equipped with embedded processing capabilities that enable localized data analysis and real-time decision support.

Each sensor module can acquire a broad range of physical and chemical parameters essential for combustion control. These include air and gas pressures, differential pressure across orifice plates, air and gas temperatures, refractory and metallic surface temperatures, vibration signatures, oxygen and carbon monoxide concentration. The integration of these diverse measurements provides a comprehensive, multi-dimensional view of each burner's operating state.

Fig. 2 – Smart sensors with enabled data pre-processing

To manage the high volume of generated data, SHP employs edge computing strategies. Data are pre-processed directly at the sensor level using embedded microcontrollers. This includes filtering, normalization, and feature extraction, which significantly reduces the data load transmitted to the central server while preserving critical information. Sensors also dynamically adjust their sampling rates based on the operational regime – whether steady-state, transient, or fault-prone – optimizing both data quality and system responsiveness.

The processed data are then analyzed using advanced algorithms, including statistical modeling, pattern recognition, and rule-based diagnostics. These tools detect deviations from nominal conditions, identify early signs of component degradation, and estimate key performance indicators such as combustion efficiency and air-fuel ratio (lambda). The system also supports the creation of virtual sensors – mathematical models that infer unmeasurable quantities such as pollutant emissions (e.g., NO_x, CO) or internal temperatures – based on correlations with historical and test data.

This intelligent data processing framework enables SHP to deliver real-time insights and actionable recommendations for process optimization, predictive maintenance, and fault prevention. By transforming raw sensor data into high-value information, SHP enhances transparency, controllability, and reliability in industrial thermal processes.

4. COMMUNICATION AND DATA MANAGEMENT

The SHP system is supported by a robust and secure communication and data management infrastructure, engineered to meet the demanding requirements of industrial environments. This infrastructure ensures reliable transmission, storage, and access to the high-resolution data generated by the smart sensor network installed on DCC digital burners.

Data acquisition begins at the sensor level, where pre-processed information is transmitted via long-range, low-power wireless communication protocols. SHP uses **LoRa** (Long Range) technology, ideally suited for industrial application due to its ability to cover large areas with minimal infrastructure. This approach reduces cabling requirements and minimizes the impact on the existing plant Ethernet network. The use of dedicated frequency bands ensures immunity from interference with other wireless systems operating within the facility.

To ensure data integrity and confidentiality, SHP incorporates secure communication protocols with encryption and authentication mechanisms. These safeguards protect sensitive process data during transmission and ensure compliance with industrial cybersecurity standards.

Once received, the data are aggregated and stored locally on a dedicated microserver. This server acts as the

central repository for both real-time and historical data, eliminating the need for cloud-based storage and ensuring full control over data ownership. The local storage architecture also enhances system resilience, allowing continuous operation even during network disruptions.
The microserver is equipped with a lightweight, high-performance database management system optimized for high-frequency data logging and rapid retrieval. Authorized users can access the data through a secure web-based interface that supports advanced querying, trend analysis, and data export. This enables in-depth diagnostics, performance benchmarking, and long-term process optimization.
In summary, SHP's communication and data management framework combines wireless flexibility, cybersecurity, and local data sovereignty to deliver a scalable and dependable solution for real-time thermal process monitoring and control.

5. WEB INTERFACE AND USER INTERACTION

A key component of the SHP system is its intuitive, feature-rich web interface, which serves as the primary point of interaction between users and the monitoring infrastructure. Designed for usability and operational efficiency, the interface enables real-time supervision, diagnostics, and control of DCC digital burners from both local and remote locations.
Hosted on a dedicated microserver within the plant network, the interface ensures secure, low-latency access without relying on external cloud services. It is accessible via standard web browsers and requires no proprietary software, allowing seamless integration into existing IT environments.
Functionally, the interface provides comprehensive visualization of real-time process data, including temperature profiles, pressure readings, flow rates, and combustion efficiency metrics – see Fig. 3. These parameters are displayed through dynamic dashboards, customizable charts, and trend plots, enabling operators to monitor burner performance at a glance. Historical data overlays support comparative analysis and the identification of long-term trends or deviations – see Fig. 4.

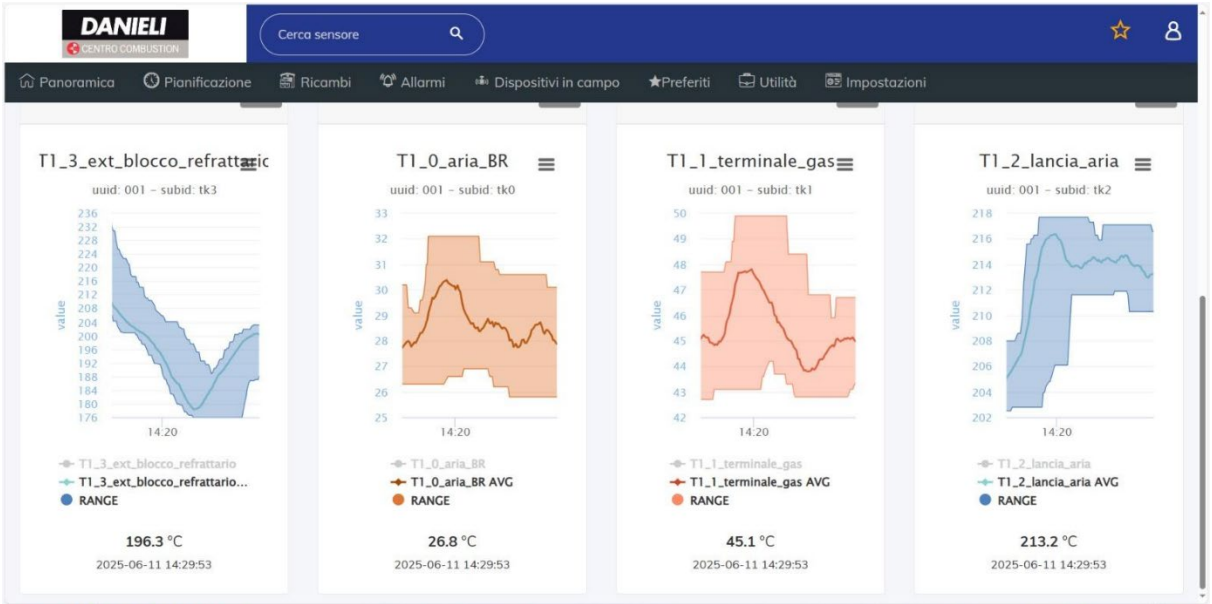

Fig. 3: Example of real time data acquisition of various parameters:

- Refractory block temperature
- Burner body external temperature
- Gas lance tip temperature
- Air duct temperature

Fig. 4: Example of historical data acquisition of various parameters:

- Burner body external temperature
- Gas lance tip temperature
- Air duct temperature
- Refractory block temperature

The system also features an intelligent alerting mechanism that notifies users of anomalies, threshold violations, or predicted failures based on sensor data and algorithmic analysis. Alerts are categorized by severity and include diagnostic information and recommended corrective actions, supporting timely and informed decision-making.

Additionally, the interface includes robust reporting tools that allow users to generate and export detailed performance summaries, maintenance logs, and compliance documentation. Reports can be customized by time range, data granularity, and content, making them suitable for both operational and managerial use.

To ensure data security, the SHP interface supports user authentication and role-based access control, restricting access to sensitive functions and data to authorized personnel only – an essential feature in industrial environments where data integrity and operational security are paramount.

Overall, the SHP web interface transforms complex sensor data into actionable insights through a user-centric design, enhancing situational awareness, operational responsiveness, and process optimization capabilities.

6. INDUSTRIAL APPLICATION EXAMPLE

The SHP (Smart Heat Process) system is the standard monitoring platform used by Danieli Centro Combustion during burner testing at the DCC Research Center, located within the University Campus of Savona. This controlled environment provides an ideal setting for validating SHP configurations prior to deployment in large-scale industrial installations. It also serves as a live demonstration platform, allowing customers to observe SHP's capabilities firsthand during actual burner firing operations.

Several customers have taken advantage of this opportunity, leading to multiple orders for SHP installations on operational production lines. In many cases, the system's capabilities were tested and validated during the commissioning phase itself.

Since June 2024, SHP has been installed on a galvanizing line operated by a leading Italian coil producer,

whose plant is equipped with Danieli digital burners – see fig. 5. Additional installations are planned, including a tunnel furnace for bar heat treatment in the United States, several batch furnaces in Northern Europe, and potentially multiple pit furnaces in Northern Italy.

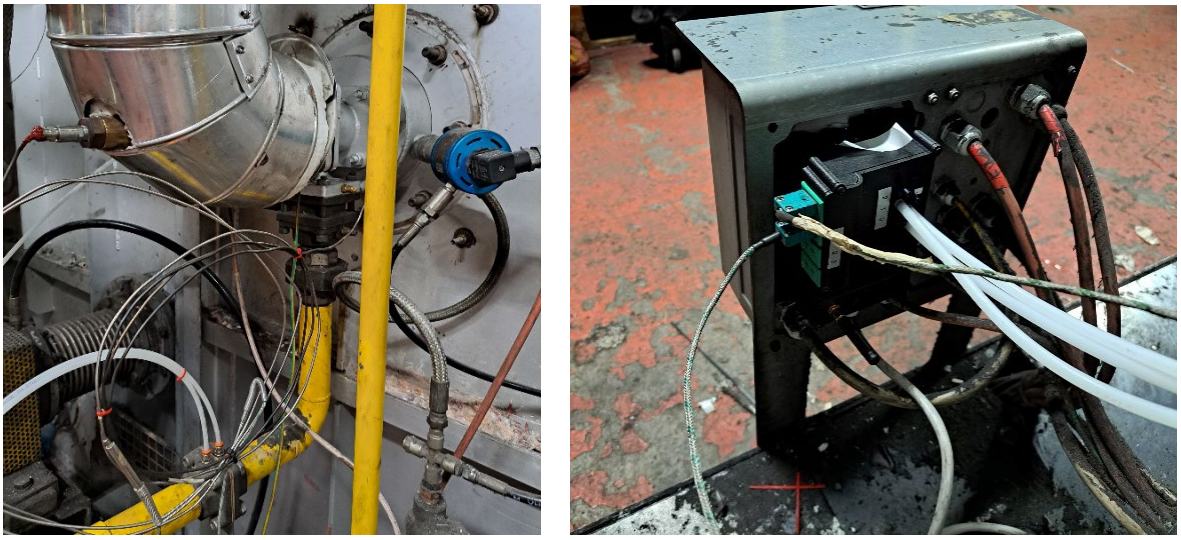

Fig. 5: Left side, example of burner with sampling points.
Right side, example of Smart Sensor for temperature and pressure

Even in its first industrial application, SHP demonstrated the intrinsic value of its technology. During commissioning of the hot-dip galvanizing line (HDGL), several burners exhibited unstable flame behavior and uneven heating, with spontaneous shutdowns occurring during startup. The commissioning team requested support from the R&D department to investigate the issue using SHP-acquired data – specifically, flow rates and temperatures in the fuel and combustion air lines.
An R&D technician remotely accessed the SHP system from the office and analyzed the data. The review identified abnormal gas pressure levels between the orifice plate and the micrometric valve used to regulate gas flow to individual burners. This insight led the commissioning team to inspect the filters upstream of the microregulators, where they discovered significant clogging caused by improper initial purging of the gas line. After cleaning and retesting the lines, pressure levels returned to normal value, and the issue was resolved. SHP enabled rapid root cause identification and immediate corrective action, significantly reducing troubleshooting time.
In this case, SHP was used reactively – after the issue had occurred. However, its true strength lies in predictive analysis. A rising or abnormally high gas pressure reading could have alerted operators to inspect the filters proactively, potentially avoiding the problem altogether.
SHP provides instant visibility into the real-time operating conditions of a plant. Its lightweight infrastructure allows for easy integration into existing systems with minimal investment and no major modifications. The system's modularity also enables scalable deployment across various plant areas.
Beyond direct measurements, SHP could infer additional performance indicators by applying advanced analytics to measured data. This enables comprehensive evaluation of burner and plant performance, supports predictive maintenance strategies, and facilitates early detection of component degradation. As a result, SHP contributes to improved process quality, enhanced thermal uniformity, and increased overall plant reliability.

ADVANTAGES AND CONCLUSIONS

The SHP system represents a paradigm shift in the management of industrial combustion processes by integrating advanced sensing, edge computing, and intelligent data analytics into a unified, autonomous platform. One of its most significant advantages is the ability to perform continuous, high-resolution monitoring of individual burners, providing real-time visibility into critical process parameters that were previously inaccessible or only indirectly inferred.

Through its data-driven optimization capabilities, SHP enables precise tuning of combustion conditions, ensuring optimal air-fuel ratios, minimizing thermal imbalances, and maintaining consistent process temperatures. These improvements translate into measurable gains in energy efficiency, with direct benefits in fuel cost reduction and operational sustainability. Additionally, the system's predictive maintenance features – powered by anomaly detection algorithms and virtual sensor modeling – facilitate early identification of component wear or process deviations, reducing unplanned downtime and extending equipment lifespan.

The platform's secure, web-based interface allows operators and technicians to monitor and control burner performance remotely, enhancing operational flexibility and enabling centralized oversight across multi-plant or distributed manufacturing environments.

From an environmental perspective, SHP contributes to emissions reduction by maintaining optimal combustion conditions and enabling rapid corrective actions in response to deviations. This supports compliance with increasingly stringent environmental regulations and aligns with corporate sustainability objectives.

SHP system offers a comprehensive, forward-looking solution for intelligent thermal process management. Its modular architecture, advanced analytics, and user-centric design make it an asset for industries that rely on DCC digital burners – particularly in sectors such as steelmaking, where process stability, energy efficiency, and environmental compliance are critical to long-term success.

ADVANTAGES OF MANUFACTURER EXPERTISE AND MACHINE SELF-LEARNING FOR EFFECTIVE PREDICTIVE MAINTENANCE OF INDUSTRIAL GEARBOXES

Alberto Scarmi – SEW Eurodrive, Germany

Industrial gearboxes are essential in steel plants, ensuring the right speed and torque for various machines. Predictive maintenance plays a key role in preventing failures and minimizing downtime. This approach is greatly enhanced by combining the manufacturer's deep expertise with machine self-learning capabilities.
The condition monitoring system integrates design data of gears, bearings, and lubrication, enabling accurate interpretation of sensor signals. This allows the system to distinguish between normal wear and potential faults, improving forecasts on component lifespan.
Self-learning algorithms further boost performance by analyzing operating states and identifying patterns through cluster analysis. Over time, the system becomes more accurate in forecasting oil levels and predicting both short- and long-term failures.
As a result, the system can automatically recommend actions and support maintenance planning, thereby reducing costs and increasing safety. It also reduces reliance on experienced personnel, as it continuously improves through data-driven learning.
This synergy between expert knowledge and adaptive intelligence offers a powerful, integrated solution for predictive maintenance in industrial gearboxes.

KEYWORDS: PREDICTIVE MAINTENANCE – MACHINE SELF-LEARNING – INDUSTRIAL GEARBOX – CONDITION MONITORING – VIBRATION ANALYSIS

INTRODUCTION: THE ROLE OF INDUSTRIAL GEARBOXES IN THE METAL INDUSTRY

In the metal industry, industrial gearboxes play a fundamental role in ensuring the smooth and efficient operation of heavy machinery. These mechanical systems are responsible for transmitting power from electric motors to various types of equipment used in processes such as continuous casting, rolling, forging, cutting, drawing, straightening and many others. They convert the high-speed, low-torque output of electric motors into the low-speed and high-torque required for the application, with torque ranging from several thousand to over a million Newton-meters. This allows machines to manipulate metal under intense conditions.
Beyond power transmission, gearboxes also serve a structural role by supporting external forces that arise during operation. These forces may come directly from the application—such as the weight of large metal parts or the impact of dynamic loads—or from auxiliary components like brakes. In many systems, gearboxes are designed to absorb and withstand these forces, helping to hold or stop the application when needed. This makes them critical not only for motion but also for stability and safety.
These functionalities must be ensured within often harsh operating environments with high temperatures, continuous use, and exposure to dust or metal particles. For these uses, robust materials, sealing and lubrication systems are employed to ensure long-term performance.
With the rise of automation, gearboxes are now often integrated with sensors and digital control systems. This integration enables real-time monitoring of multiple parameters, to assess the condition of the equipment.
Predictive maintenance takes a step further by aiming to anticipate failures and perform maintenance only when necessary, thereby avoiding both over-maintenance and unexpected breakdowns. To achieve this effectively, it is essential to combine the manufacturer's expertise with machine self-learning. The former provides a deep understanding of the gearbox's behavior and evolution, while the latter enables analysis of how the machine is used within the specific application by the operator.

KEY ASPECTS FOR GEARBOX MAINTENANCE

Effective gearbox maintenance is essential for ensuring operational reliability, minimizing downtime, and extending equipment lifespan. This involves a thorough understanding of the factors that influence gearbox performance, particularly oil condition and mechanical wear. Oil degradation can compromise lubrication and lead to component failure. Maintaining the correct oil level is equally critical, as deviations can result in inadequate lubrication and overheating. Additionally, wear of gears and bearings can cause severe damage if left unchecked. Addressing these key aspects is vital for optimizing gearbox health and performance.

Oil degradation

Oil degradation in industrial gearboxes is driven by both chemical and mechanical factors, each significantly impacting oil quality. Chemical degradation is primarily caused by elevated temperatures that accelerate oxidation. This process produces organic acids capable of corroding metal surfaces and leads to the formation of sludge and dense, sticky deposits, as well as hard, lacquer-like coatings. These can clog filters and impair lubrication efficiency. Oxidation also depletes critical additives, such as antioxidants, diminishing the oil's protective properties. Common signs of chemical degradation include oil darkening and the development of a burnt odor.

On the mechanical side, heavy loads generate high pressure and shear forces that physically break down oil molecules, reducing their molecular weight and viscosity. These forces can also neutralize or destroy essential additives. Input speed and oil temperature are key factors that influence oil quality and are crucial for predicting its remaining service life.

The combined effects of chemical and mechanical degradation result in increased metal-to-metal contact, accelerated wear, overheating, and reduced gearbox efficiency.

Oil level

Maintaining the correct oil level is essential for proper lubrication and the operational integrity of a gearbox. Deviations from the optimal level may arise due to various factors. Evaporation is common, especially at high operating temperatures, where lighter oil fractions vaporize and escape through the gearbox breather or vent. Leaks from worn seals or shaft misalignment can cause a gradual but significant drop in oil level, often going unnoticed until it becomes critical.

In systems where multiple gearboxes are interconnected, oil migration can occur if internal seals are compromised, leading to an unexpected reduction in oil level in one of the units. Aerosolization also contributes to oil loss, particularly in high-speed applications where turbulence and splashing atomize the oil into a fine mist that escapes through the breather.

Finally, improper maintenance, such as overfilling or underfilling during oil changes, directly results in incorrect oil levels. Any deviation from the correct oil level compromises lubrication and can severely affect the performance and longevity of the gearbox.

Wear of gears and bearings

Mechanical fatigue wear is a critical failure mechanism affecting both gears and bearings, developing over time due to repeated cyclic loading.

For gear flank pitting, the primary cause is repeated contact stress between meshing gear teeth. This involves high localized pressure, known as Hertzian stress, which initiates subsurface micro-cracks. Over time, these cracks propagate, causing small fragments of material to detach and form pits. The resulting surface roughness leads to uneven load distribution, increased noise, vibrations, and accelerated wear.

In the case of gear tooth bending, the failure is caused by repeated bending stress at the root of the gear tooth during torque transmission. Stress concentrations at the root initiate cracks that grow with each load cycle, eventually leading to complete tooth fracture. This can result in sudden gear failure and potentially cascading damage within the gearbox.

Bearing pitting arises from repeated rolling contact between bearing elements (balls or rollers) and raceways. Cyclic stresses generate subsurface cracks in the raceways, which eventually reach the surface, causing material flaking or pitting. These defects typically appear on the raceways or rolling elements and lead to increased vibration, noise, loss of smooth rotation, and a heightened risk of catastrophic failure.

GEARBOX SET-UP FOR PREDICTIVE MAINTENANCE

For the purpose of this dissertation on predictive maintenance, it is assumed that the gearbox is equipped with a range of sensors for condition monitoring. This approach is inspired by SEW-EURODRIVE's implementation of predictive maintenance in industrial gearboxes through the development of the DriveRadar® system, which serves as a reference model for this paper.
Key operational parameters are:

- Ambient Temperature
- Oil Sump Temperature
- Oil Level, determined with millimeter precision using an ultrasonic tank sensor (ultrasonic transmitter)
- Input Speed, measured by an inductive pulse sensor, which detects both the speed and direction of rotation. From these measurements the speeds of all other rotating components within the gearbox are also determined
- Vibration Acceleration and Velocity, using a high-resolution acceleration sensor, able to capture a broad frequency spectrum, enabling precise analysis of vibration data during gearbox operation.
- Input Torque, which can be measured depending on the installation using various methods, each with different levels of precision:
    - Calculated torque from power and speed, using electrical power measured via amplifier and current transformer in mains operations
    - Measured torque at the frequency inverter
    - Direct torque measurement via an external measuring system, offering the highest precision

PREDICTIVE MAINTENANCE

Predictive maintenance of gearboxes is a cutting-edge approach that leverages real-time data, advanced analytics, and machine learning to optimize the performance and longevity of gearbox components. By continuously monitoring parameters such as oil temperature, oil level, vibration patterns, and mechanical stress, the system can forecast potential failures before they occur.

Oil remaining service life

The calculation of the remaining service life of a gearbox oil is based on real-time measurements of oil temperature and the actual operating time of the gearbox. By continuously monitoring temperature variations—arising from the gearbox's specific operating conditions—the system constructs a temperature-time duty cycle. This cycle is then used to compute the cumulative thermal stress experienced by the lubricant.
The model is continuously refined based on extensive field experience, which is progressively expanded through ongoing collaboration with customers.

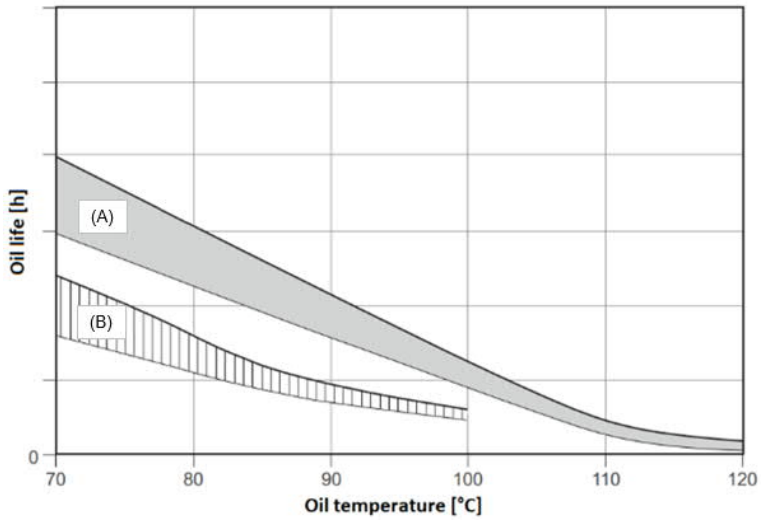

Fig.1 – Oil life vs. oil temperature dependence. (A) Synthetic PAO oils, (B) Mineral oils

This combination ensures that the thermal aging forecasts are realistic and aligned with the actual operating conditions in the gearbox. To predict the optimal timing for an oil inspection or, when necessary an oil change, the Edge Processing Unit (EPU) of the system records the historical operating data and sends it to a data center, where linear regression is performed to extrapolate the trend of the remaining oil life over time. This predictive approach allows for proactive maintenance scheduling, reducing the risk of unexpected failures and extending the operational efficiency of the gearbox.

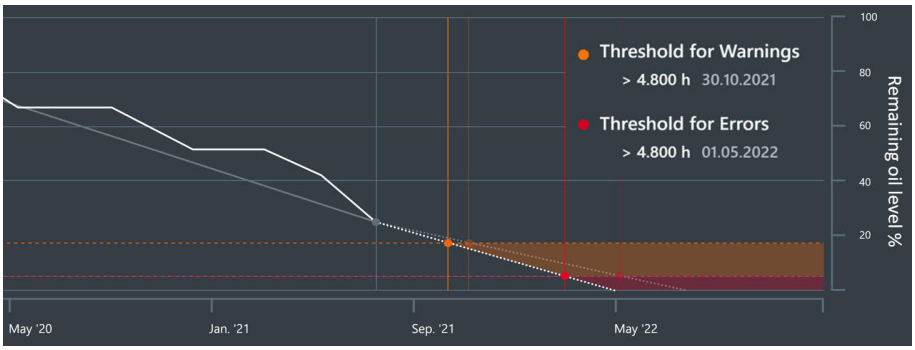

Fig.2 – Oil remaining service life forecast

Oil level forecast

The oil level of the gearbox is measured using an ultrasonic sensor. To monitor and predict trends in the oil level, an Edge Processing Unit (EPU) records operational data and transmits it to a data center, where several parameters are evaluated: the oil level itself, oil temperature, and the input shaft's speed, acceleration, and direction of rotation.

Machine learning is initiated after the gearbox is commissioned. During a 100-day learning phase, the system uses cluster analysis to identify patterns and correlations between the oil level and the aforementioned parameters. This analysis culminates in the development of a linear regression model, which is then used to extrapolate oil level forecasts for defined operating conditions.

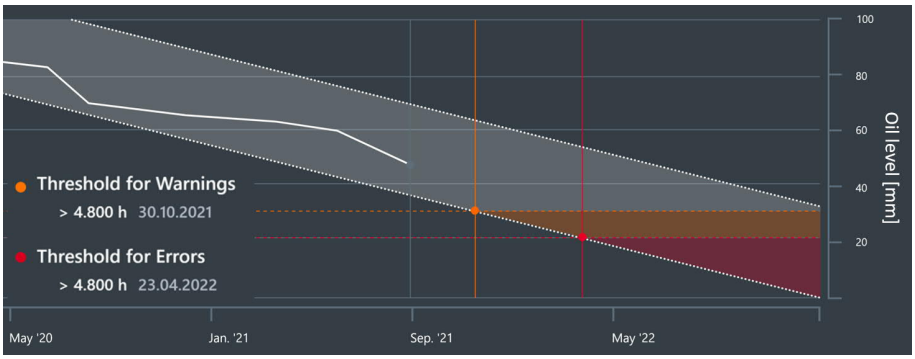

Fig.3 – Oil level monitoring and forecast

The use of machine learning and cluster analysis offers significant advantages, particularly in high-dynamic drive systems. Without it, a simple average of the oil level would be misleading, especially when attempting to extrapolate trends over time for reliable forecasting. In contrast, this model compensates for fluctuations in oil level caused by changes in speed, direction of rotation or temperature-induced volume changes.

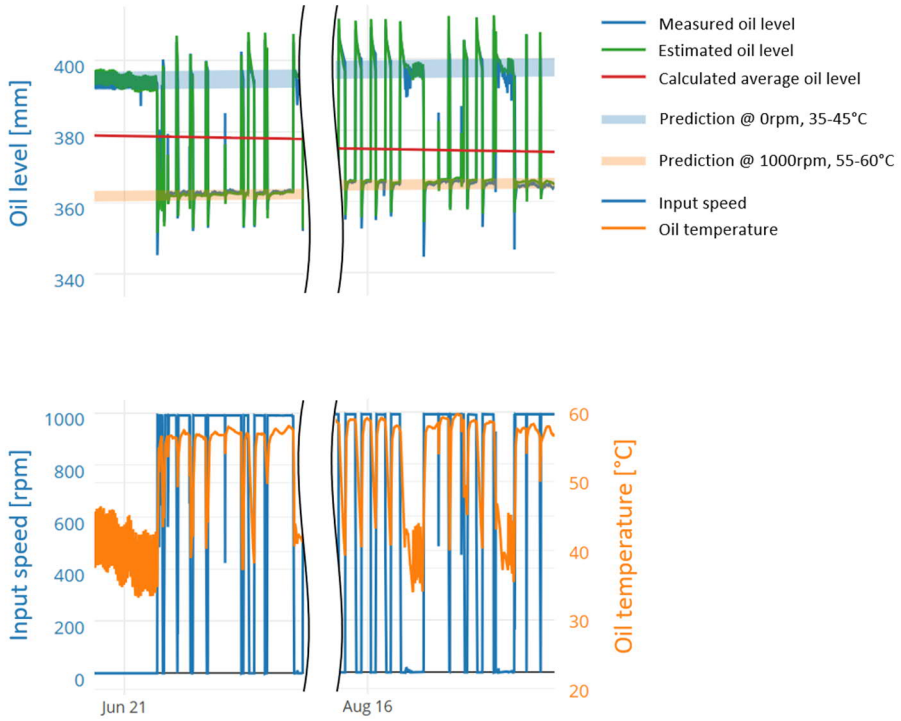

Fig.4 – Influence of temperature and speed on the oil level

As the database of collected measurements grows, the self-learning system becomes increasingly effective at recognizing operating states, thereby enhancing predictive accuracy.
It is therefore possible to detect and monitor actual changes in oil volume, caused by unnoticed leaks or evaporation as previously explained, allowing for timely and measured interventions—well before traditional systems, such as float switches, would signal dangerously low oil levels.

Gears and bearings life forecast

For gears and bearings, the forecast of long-term failures is closely tied to the overall gearbox design. The calculated design of the gearbox is directly compared with the actual measured operating conditions. The

underlying calculation model incorporates statistical failure probabilities to estimate the remaining service life based on the average utilization of the drive.
A central component of this forecast is SEW's internal gearbox mechanical calculation model, Wesilab. This advanced model is the same one used during the initial verification of customer application data to select the appropriate gear size and configuration. In the context of predictive maintenance, Wesilab applies its detailed mechanical calculations to assess gearbox components during actual operation.
The model integrates extensive manufacturer expertise, precisely computing factors such as:
Gear geometry and micro geometry (including lead and profile modifications), bearing preload and stiffness, shaft bending and torsion, housing stiffness and thermal deformations.
These parameters are all computed to calculate mechanical stress within each component, in accordance with DIN and ISO standards.
From measured load and speed data, the system constructs a duty cycle, enabling the calculation of bearing loads, gear flank pressure, and gear root stress. Fatigue damage is then assessed using the S-N curve (Stress vs. Number of cycles) for each component, determining its remaining service life.
This extrapolated service life provides a forecast of operating hours before specific failures—such as gear flank pitting, bearing raceway damage, or gear tooth cracking—begin to occur and propagate.
While long-term failures are predicted through mechanical modeling, short-term failures are addressed via vibration monitoring and analysis. Damage detection primarily relies on vibration analysis, where vibrations propagate from their source to the gearbox housing and are captured by an acceleration sensor. The transmission path includes the gear mesh, shaft, bearing inner ring, bearing rolling elements, bearing outer ring, and gearbox housing.

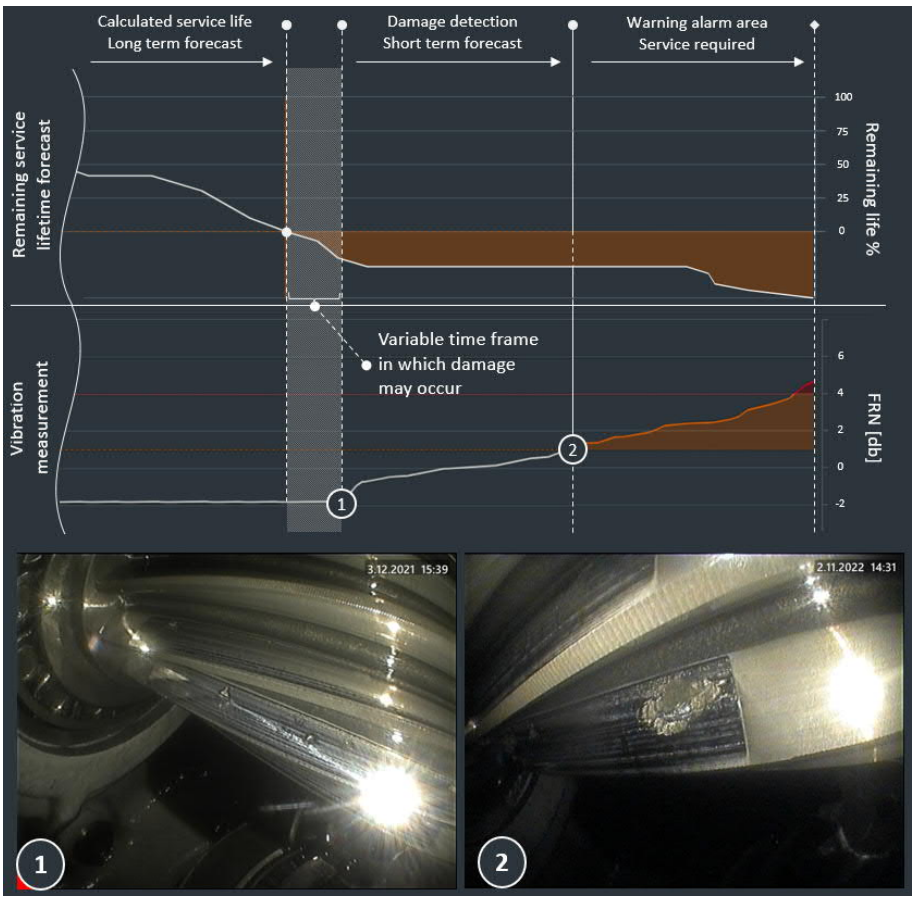

Fig.5 – Gear pitting forecast and actual detection

Vibrations are analyzed using order analysis, which normalizes the frequency spectrum relative to rotational

speed, making it independent of gearbox speed. Each type of damage has a characteristic defect order in the spectrum, acting like a fingerprint to precisely locate the damage—such as a pit on a gear flank or a defect on a bearing raceway.
This capability is enabled by the manufacture’s pre-stored kinematic data for every shaft, gear, and bearing, including the number of shafts, gear tooth counts, and bearing internal geometry data.
After gearbox commissioning, the system enters a self-calibration phase known as the "teach-in mode". During the first 100 days, the DriveRadar analyzer computes trend values and establishes defect-specific thresholds for each component. It calculates average values and standard deviations to define warning and alarm limits. Continuous monitoring of these relative trends is essential, as it filters out external disturbances from the operating environment, ensuring accurate and reliable diagnostics.

SUMMARY

The effective predictive maintenance of industrial gearboxes hinges on the crucial integration of manufacturer expertise with machine self-learning capabilities. This combined approach elevates condition assessment beyond mere monitoring, providing a more accurate and insightful understanding of a gearbox's health.
Manufacturer expertise provides the foundational design and calculation data for drive components, such as gears and bearings, and oil properties. This deep understanding enables the system to intelligently interpret sensor data. It is essential for generating realistic oil residual service life forecasts continuously refined with field experience, and for long-term failure forecasts of gears and bearings. This expertise also underpins precise vibration analysis for damage detection.
Concurrently, machine self-learning algorithms continuously enhance predictive accuracy by analyzing operating states and patterns. During a learning phase these algorithms identify correlations and accurately forecast parameters like the oil level.
Ultimately, this synergy maximizes component utilization, streamlines maintenance planning, reduces downtime and costs, and enhances safety, while decreasing reliance on experienced service staff.

Harnessing Data Lakes for Global Maintenance Service: Insights and Improvements through Advanced Data Analysis

Name(s) of the author(s) – Affiliation(s), Country
Ing. Michael Weinzinger – Primetals Technologies, Austria
Hugo Teixeira Veiga – Primetals Technologies, Brazil
Nicholas Comstock – Primetals Technologies, USA
DI Klaus Frauenhuber – Primetals Technologies, Austria
Franz Kolmbauer – Primetals Technologies, Brazil
DI Florian Hollensteiner – Primetals Technologies, Austria
DI Dr. Gerald Hohenbichler – Primetals Technologies, Austria

In the era of big data, organizations are increasingly leveraging data lakes to store vast amounts of unstructured and structured data. This paper explores the transformative potential of data lakes in the context of global maintenance services. By integrating advanced data analysis techniques, we aim to uncover actionable insights that drive service improvements across various locations and technologies. Our study examines the methodologies for effective data lake management, the challenges of data integration, and the benefits of real time analytics in maintenance service operations. Through case studies and empirical data, we demonstrate how digital transformation in maintenance can achieve significant performance enhancements and maintain a competitive edge in the global market. This research contributes to the growing body of knowledge on data driven decision making and offers practical recommendations for leveraging data lakes to optimize service delivery.

KEYWORDS: ASSET TRACKING - MAINTENANCE STRATEGIES - MAINTENANCE SERVICE - DATA LAKE - DATA ANALYTICS

INTRODUCTION

The industrial landscape is experiencing a transformation fueled by the rise of big data, IoT, and intelligent systems. Maintenance operations, historically viewed as cost centers, are now becoming strategic assets in the digital economy. The ability to harness real-time data and predictive analytics is a key differentiator in competitive service environments.

Data lakes enable holistic data management by consolidating sensor feeds, Enterprise Resource Planning (ERP) systems, Computerized Maintenance Management System (CMMS) logs, digital twin outputs, and human feedback within a single ecosystem. They support high-scale storage and facilitate complex, ad-hoc analytics—unconstrained by traditional schema restrictions.

This paper investigates how maintenance service providers like PTTS (Primetals Tangshan Technology Services) and Primetals Technologies (servicing Ternium Brazil and others) can translate predictive indicators into actionable maintenance orchestration, optimizing both operational outcomes and strategic business performance. We introduce a comprehensive framework, evaluate performance trends via simulated benchmarks and explore future extensions toward intelligent service orchestration using GenAI.

BACKGROUND AND MOTIVATION

Limitations of Traditional Maintenance

These approaches are increasingly untenable in complex industrial settings with tight uptime requirements and global service obligations.

- Reactive maintenance leads to frequent production interruptions and cost unpredictability.
- Time-based maintenance often results in unnecessary part replacements and labor expenses.

Condition-Based and Reliability Centered Maintenance

The convergence of these methodologies with Industry 4.0 technologies enables a rational and efficient maintenance strategy.

- Condition Based Maintenance (CBM) uses asset data to drive maintenance timing.
- Reliability Centered Maintenance (RCM) prioritizes failure modes based on severity, safety, and cost.

The Data Lake Advantage & Benefit

Schema flexibility allows storing disparate data forms (vibration, image, text, logs) without upfront transformations. Scalability and near real-time ingestion support high-velocity data streams and open architecture encourages the integration of advanced tools and digital twins.

Business Motivation and Complexity

The motivation to adopt data lake-enabled maintenance stems not only from operational efficiency goals but also from evolving business models and service expectations:

- In traditional manufacturing, maintenance is often viewed as a cost center. However, for service providers like Primetals Technologies, maintenance is a core business and profit-generating function.
- This shift demands enhanced visibility into asset behavior, resource optimization, Service Level Agreement (SLA) adherence, and cost-performance balancing—across diverse client operations and geographies.
- Organizational complexity, driven by customer-specific requirements, contract variations, and equipment diversity, further necessitates a data-driven, customizable, and intelligent maintenance infrastructure.

METHODOLOGY

System Architecture and Data Flow

Our system adopts modern Data Lake architecture, combining scalability with structured query capabilities. Ingestion pipelines bring in Enterprise Resource Planning (ERP) updates, Computerized Maintenance Management System (CMMS) work orders, sensor data streams, digital twin insights, and technician notes. These data are aligned and tagged with metadata for context.

Governance and Quality Framework

We enforce a robust data governance model, including:

- Role-based access control (e.g., planner, technician, administrator).
- Metadata catalogs with asset identifiers, failure modes, and maintenance history.
- Audit trails enabling regulatory compliance.

Standardized data schemas and frequent integrity checks (e.g., anomaly detection, validation rules) maintain data quality.

Analytics, Modelling, and Orchestration

Failure Mode and Effect Analysis (FMEA) -driven failure mode indexing enables asset-specific diagnostics. Machine learning models analyze sequence patterns related to failure progression and feedback directly into CMMS work order generation scripts. A simulation engine allows scenario planning for multi-customer SLA decisions.

Generative Artificial Intelligence (GenAI)- Driven Interface Layer

From Data Abundance to Decision Confidence in high-volume industrial environments, maintenance professionals face the challenge of discerning which piece of data, or which anomaly is relevant now. Raw sensor streams, work order histories, and ERP information can overwhelm rather than inform. We address this challenge through a layered approach:

- Contextual dashboards prioritize only those failure modes currently trending toward threshold.
- Rule-based alert suppression filters out redundant or self-resolving anomalies.
- Intervention scorecards weigh urgency, cost, and resource impact to guide attention.

Additionally, the GenAI interface supports just-in-time explanation, enabling users to ask:
“Why is this being recommended?” or “What’s changed since the last inspection?”
This design ensures that not only data is provided but curates knowledge, presenting the right information, to the right person, at the right moment.

A conversational GenAI agent, grounded in failure-mode logic, can:

- - Interpret asset health ("fatigue detected; vibration increasing.")
- - Recommend actions ("Schedule bearing inspection and initial lubrication by end of shift.")
- - Simulate outcomes ("If delayed, probability of shutdown in 72 h increases by 15%.")

RESULTS AND DISCUSSION

The deployment of the MAT (Maintenance Asset Technology) platform has delivered measurable operational improvements, while also highlighting key principles in digital maintenance transformation. This section outlines how actionable orchestration, field implementation, advanced analytics, and GenAI readiness converge to support intelligent, precise, and scalable maintenance practices.

What is MAT

MAT is a comprehensive software solution developed by Primetals Technologies for managing industrial maintenance operations. It functions as both a Computerized Maintenance Management System (CMMS) and an Enterprise Asset Management (EAM) platform, designed to optimize asset reliability, streamline maintenance workflows, and reduce operational costs.
MAT supports the full lifecycle of plant maintenance from failure detection to resolution by integrating various systems such as condition monitoring, ERP, and automation platforms. It enables predictive, preventive, and reactive maintenance strategies, and provides actionable insights through advanced analytics and reporting tools.

Actionable Maintenance Orchestration

One of MAT’s central capabilities is the ability to bridge the gap between diagnostic insight and maintenance execution. Traditional predictive systems often stop at anomaly detection. MAT continues to generate intervention-ready tasks tailored for CMMS integration.
The system delivers:

- Task recommendations directly aligned with CMMS fields, defining priority, labor hours, spare parts, and sequencing.
- Orchestration logic that accounts for technician availability, asset accessibility, and safety constraints.
- Feedback mechanisms, including technician annotations and asset condition reassessment, that support continuous learning and system adaptation.

This results in a shift from alert-based workflows to actionable maintenance orchestration, where each recommendation can be confidently planned, resourced, and executed.

Embedding Precision Maintenance in Data-Orchestrated Workflows

As organizations move from reactive and preventive paradigms to predictive and prescriptive maintenance, a new requirement emerges. Ensuring that interventions are executed with engineering-grade precision. Precision Maintenance refers to the consistent application of manufacturer specifications, validated procedures, and calibrated tools to achieve optimal reliability outcomes. In the MAT platform, this is supported through digitally standardized work procedures, integrated within CMMS and aligned to ISO or Original Equipment Manufacturer (OEM) specifications. Tool validation checklists and calibration routines, ensuring task readiness and compliance. Instructional overlays embedded in digital work orders, guiding technicians on tolerances, torque values, alignment techniques, and other critical execution variables.

Tasks such as bearing replacement or shaft alignment are elevated from routine activities to high-value, reliability-critical actions. Precision Maintenance not only improves outcome consistency but also establishes a structured knowledge base for future automation. These procedures form the blueprint for future GenAI agents, enabling them to simulate interventions, verify compliance, and coach technicians through interactive, stepwise guides.

Real-Time Agents and Closed-Loop Learning

MAT dashboards are dynamic, layered analysis environments that support ongoing model refinement and decision contextualization. They include Failure mode tagging, allowing asset behaviors to be interpreted through FMEA logic and historical trends. Priority-ranked dashboards, highlighting interventions with resource loads, SLA impacts, and execution urgency. Closed-loop feedback with post-action sensor data confirms or invalidates remedial effectiveness. Ineffective interventions trigger model retraining events and anomaly escalation reviews. This architecture sets the foundation for GenAI integration, where agents are able to generate conversational, context-aware recommendations grounded in real-time condition data.

Navigating Correlation and Causation in Predictive Maintenance

While predictive maintenance analytics often rely on high-volume sensor correlations, it is vital to distinguish statistical association from physical causality. For example, an observed correlation between vibration amplitude and component failure does not necessarily imply a causal mechanism, especially in multi-factor systems. To guard against overfitting and false positives, MAT incorporates safeguards through FMEA-driven root cause structures tie alerting patterns to validated degradation pathways. Technician feedback loops confirm whether a recommended intervention resolved the issue and Human-in-the-loop decision protocols require expert approval for automation-triggered tasks.

This hybrid approach ensures that predictive analytics do not displace engineering judgment but augment it with traceable, explainable, and testable insights. It also lays the groundwork for GenAI agents to operate within trusted, logic-bound parameters, ensuring safe and effective collaboration with human decision-makers.

CHANGE MANAGEMENT AND DIGITAL TRANSITION

The successful implementation of a data lake-driven maintenance platform such as MAT requires not only technical integration, but a deep and deliberate organizational transformation. Digital maintenance orchestration disrupts long-standing habits, workflows, and assumptions. Therefore, change management must encompass people, processes, and culture, ensuring that new technologies translate into sustained operational improvement.

Stakeholder Engagement

The widespread adoption of MAT has been achieved through strategic stakeholder engagement across all organizational levels. Multilayer training programs have been developed for technicians, planners, reliability engineers, and executives. These include hands-on onboarding, use-case demonstrations, and interactive simulations. Governance committees ensure alignment between Information Technology (IT), maintenance, and business objectives, while maintaining data quality and compliance standards. A regional champion model has proven instrumental in fostering local ownership. These champions serve as platform advocates, trainers, and feedback conduits, bridging corporate intent with operational reality. This distributed approach balances central direction with local empowerment, accelerating buy-in and platform maturity.

CMMS Restructuring and Process Integration

The shift from traditional, schedule-based maintenance to data-driven orchestration required significant restructuring of CMMS workflows. Key changes include transitioning from time-based to event-driven work orders, triggered by real-time asset health insights, failure mode predictions, and system thresholds. Integration of predictive planning logic into CMMS task generation, including work prioritization, labor allocation, and spare part reservations and Cross-functional coordination across maintenance, production, procurement, and IT to ensure seamless data flows and operational alignment.

These changes reposition CMMS from a documentation tool to a decision-support and task orchestration system, enabling more agile and targeted interventions.

Adaptive and Role-Based User Interfaces

Adoption at the operational level is supported by intuitive, role-specific interfaces, designed to align with daily workflows and decision contexts. A mobile application provides field technicians with on-the-go access to asset status, task instructions, checklists, and conversational interaction with GenAI agents. Users can update work progress, capture notes, and close tasks, all in real time.

Role-based dashboards present relevant Key Performance Indicators (KPI), and alerts tailored to planners, engineers, or executives, avoiding data overload while maintaining situational awareness. They include interactive elements such as failure mode visualization and task traceability support closed loop learning and engagement.

These tools ensure that data is not only available, but also understandable, actionable, and contextually meaningful.

Cultural Transformation and Human-Centered Artificial Intelligence (AI)

Digital maintenance transformation is not solely a technical journey; it is a cultural shift. Success requires a reframing of organizational attitudes toward data, automation, and AI. Early success stories, such as avoided failures, reduced downtime, and high-impact interventions, are shared within teams to illustrate value and build trust. Technician contributions to improving models, refining checklists, and shaping dashboards are recognized and rewarded. The GenAI agent is framed not as a replacement, but as a collaborative assistant, supporting decision-making and knowledge retention. This approach promotes a culture of continuous learning, in which human expertise is enhanced, not displaced, by intelligent systems.

Embracing Contextual Knowledge and the Power of Simple Questions

One of the most important lessons from MAT's global deployment is the recognition that there is no “one-size-fits-all” solution when it comes to checklists, reports, or dashboards. Maintenance knowledge is inherently context-dependent, influenced by asset characteristics, technician experience, regional regulations, and organizational maturity.

Efforts to impose standardized reporting structures across all sites often result in:

- Reduced adoption due to irrelevance or complexity.
- Incomplete data entry that undermines decision support.

MAT addresses this through a flexible knowledge architecture:

- Templates are adaptable, allowing local teams to adjust procedures while maintaining core compliance.
- Dashboards are modular, exposing only the indicators relevant to each user’s role or location.
- Checklists are dynamic, updated continuously through technician feedback and analytics-based refinement.

At the same time, the platform embraces the reality that simple questions are often the most difficult, and important, to answer:

- “What did we actually do to improve this situation?”
- “Which intervention truly reduced downtime or failure recurrence?”
-

Answering these requires more than data, it requires narrative insight and causal understanding. To support this, MAT includes post-intervention annotations, where technicians can describe what was done and whether it worked. Action impact summaries, connecting tasks to changes in asset condition or performance and AI-supported retrospectives, offering structured reviews of interventions, including effectiveness scores and deviation analysis. By recognizing that learning is both data-driven and human-informed, the MAT platform evolves from a control system into a continuous learning system, capable of adapting to local needs while reinforcing global standards of excellence.

STRATEGIC IMPACT AND FUTURE OUTLOOK

The deployment of the MAT platform and its supporting data lake architecture has yielded significant strategic benefits, not only at the asset and operational level but also across financial planning, customer satisfaction, and long-term organizational learning. The following subsections detail the most prominent areas of impact and outline future development trajectories.

Operational Excellence

Implementation of data-driven maintenance orchestration has led to substantial performance gains, including a 25–30% reduction in reactive maintenance, resulting from predictive task scheduling and early interventions. Up to 18% cost savings in logistics, driven by optimized spare parts forecasting and minimized urgent deliveries. Extended asset lifespans and greater operational stability, due to precision-executed maintenance

and condition-based task planning. These improvements underscore the value of transitioning from traditional maintenance models to data-augmented, proactive service delivery.

Asset Portfolio Optimization

The integration of asset-level analytics with enterprise-level planning tools enables more strategic management of maintenance assets. Scenario modeling supports long-term capital planning, including equipment replacement or modernization strategies. Risk simulations, informed by historical failure trends and condition monitoring data, assist in prioritizing high-impact interventions and investment decisions.

Scalable Deployment with MAT "Lite"

To support smaller facilities or less digitally mature sites, a cloud-native, lightweight version of the MAT platform, MAT Lite, has been developed. This version maintains core functionality while minimizing infrastructure requirements and offering simplified user interfaces for low-code environments, Mobile-first deployment for field access and Seamless upgrade paths to full MAT capabilities as sites evolve.

Integration with Building Information Modelling (BIM) and Engineering Models

Future enhancements include the integration of MAT with BIM platforms, enabling spatially contextualized diagnostics, linking maintenance events to physical locations and 3D representations of plant environments. Improved lifecycle tracking, where asset status, location, and intervention history can be visualized in engineering-grade models to enhance planning for retrofits, facility expansion, and layout optimization.

Advancing GenAI Maturity

The GenAI agent layer will continue evolving to support increasingly intelligent interactions with users and assets. Planned capabilities include

- Diagnostic conversations that interpret real-time asset data.
- Stepwise task guides are embedded in digital work orders.
- Risk simulation models, guiding decisions based on expected outcomes.
- Natural language dialogue, enabling users to ask, "What is wrong with this pump?" or "What's the safest fix today?" and receive grounded, contextual answers.

Business Simulation in Outsourced Maintenance Models

For service providers like Primetals Technologies, which operate under outsourced maintenance contracts, the MAT platform serves as a strategic simulation engine. It supports decisions where urgent service requests risk disrupting planned operations.

Key simulation capabilities include:

- Visualizing current workloads and pending tasks across multiple sites and clients.
- Detecting resource saturation, such as labor conflicts for critical skills or bottlenecks in component availability.
- Evaluating multiple response scenarios, from internal overtime, subcontracting, or deferral, against financial and operational impact.
- Forecasting key metrics, such as lead times, SLA risks, and collateral delays on other service contracts.

For example, when a customer demands expedited delivery of a critical repair, planners can model:

- The direct cost trade-off between internal overtime and third-party subcontracting.
- The downstream impact on other clients if resources are reassigned.
- The profitability delta across multiple scenarios, including SLA penalties, expedited logistics, and labor fatigue.

This enables planners to make evidence-based, profit-conscious decisions, elevating CMMS functionality from task tracking to strategic orchestration and scenario planning.

Predictability and Profitability in Maintenance Outsourcing

Succeeding in a service model that combines performance accountability and cost efficiency requires two critical capabilities:

- Predictability: Accurately forecasting labor, materials, and task durations based on real-time and historical data.
- Profitability simulation: Assessing operational scenarios not only for feasibility but also for financial optimization.

The MAT ecosystem meets these requirements by delivering real-time insights and embedding cost-impact models within scheduling tools. This allows for:

- Balanced decision-making under dynamic conditions.
- Integrated visibility across clients and contracts.
- Scalable execution grounded in operational intelligence.

In this model, maintenance becomes not just a service, but a business operation optimized through digital tools and enterprise-level insight.

Global Standardization with Local Flexibility

One of the most significant strategic challenges is deploying a common maintenance platform across diverse global sites. While the business goals remain consistent, reliable service, cost efficiency, SLA compliance, the execution varies substantially by region.

Examples of regional variation include:

- Sites in Europe operating highly automated diagnostics and dashboards.
- Facilities in Asia rely more heavily on manual inspection and paper-based processes.
- Different client expectations regarding reporting frequency, regulatory documentation, or system integration.

To address this, MAT offers:

- A modular architecture, with centralized analytics and customizable local interfaces.
- A federated governance model, combining global standards with regional implementation ownership.
- Cross-site benchmarking tools, allowing continuous learning without enforcing uniformity.

This approach empowers each location to operate within its own digital maturity and business context, while still contributing to a cohesive, globally scalable maintenance strategy.

CONCLUSION AND RECOMMENDATIONS

Our findings affirm that maintenance-as-a-service can be elevated from cost center to strategic differentiator through data lake orchestration, CMMS-integration, RCM alignment, and GenAI collaboration.

1. Develop embedded failure mode indexes aligned with maintenance knowledge.
2. Orchestrate tasks via CMMS based on real time insights.
3. Build feedback mechanisms for reliability and model refinement.
4. Simulate multi-dimensional scenarios for business trade-offs.
5. Invest in human AI collaboration to support technician trust.

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DEVELOPMENT OF DIGITAL TOOLS AT HYBRIT´S PILOT PLANT FOR H2 DIRECT REDUCTION

Henrik von Schenck, Reine Granström, Anders Ekerot, Milan Zlatkovikj

HYBRIT Development AB, Sweden

The HYBRIT initiative was launched in 2016 by SSAB, LKAB and Vattenfall with the aim of creating a completely fossil-free value chain from mine to steel, using fossil-free electricity and hydrogen. The focus of technical development has been to build up expertise and to set the technical prerequisites for implementing HYBRIT's fossil-free value chain in full-scale production. Large parts of the development work have been carried out in facilities that correspond to full-scale industrial production environments in terms of both equipment and process control, but with lower production capacity.

HYBRIT's pilot plant for direct reduction (DR pilot) has capacity of approximately 1 tonne DRI/hour and has produced more than 5000 tonnes of fossil-free sponge iron since 2021. Data collected from pilot trials include process data, for instance detailing conditions for input and output streams, as well as measurements and material sampling from inside the DR pilot shaft (referred to as reactor excavations). This data has provided a unique and solid foundation for developing accurate multiphysics models of the H2 direct reduction process. Simulations have in turn supported process understanding and process development.

To leverage the investments in digital tools and extend their utility, efforts have been made to overcome the typically long execution times of detailed models of strongly coupled processes. Fast and accurate models have been developed by training deep neural network (DNN) models on data sets from high-fidelity physics-based models. In addition, the tools´ graphical user interfaces have been tailored based on needs and feedback from engineers and technical staff working at the DR pilot plant. So far, digital applications have been developed for on-line process monitoring and for evaluating process responses in "what-if" scenarios. The applications have been tested successfully during pilot trials running continuously for 6-8 weeks.

The workflow of digital tool development is schematically illustrated in Figure 1 below.

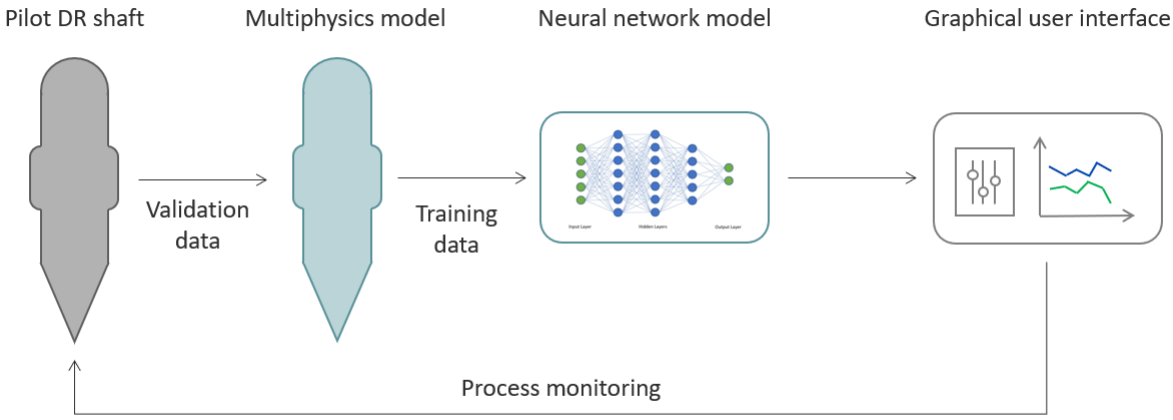

Fig.1 - Workflow of digital tool development at HYBRIT's pilot plant for H2 direct reduction.

KEYWORDS: HYDROGEN REDUCTION – PILOT PLANT – MULTIPHYSICS MODELLING – NEURAL NETWORK MODELS – DIGITAL TOOLS – PROCESS MONITORING

PCIXPERT: BOOSTING EFFICIENCY AND RESOURCES UTILIZATION

Yasmine Iciriddir – SMS group, Luxembourg
Bernard Cauwenberghs – SMS group, Luxembourg
René Gaiola – SMS group, Luxembourg
Pierre Mahowald – SMS group, Luxembourg

This paper presents the development and implementation of the Pulverized Coal Injection Monitoring Service (Paul Wurth PCIXpert), an innovative solution designed to enhance the operational efficiency and reliability of Pulverized Coal Injection (PCI) plants. The Paul Wurth PCIXpert system addresses the challenges faced by maintenance and process management personnel in monitoring complex PCI installations. The service provides a continuous evaluation of PCI transport performance through the use of key performance indicators (KPIs) and a smart alarm analysis tool.
Paul Wurth PCIXpert introduces a novel approach to the industry by offering a comprehensive, long-term analysis of the entire coal injection transport system, from storage bin to injection lances. This system is distinguished by its use of industrial dashboards and KPIs, enabling users to easily assess plant performance and identify deviations from optimal operation. The process-impact oriented alarm management system categorizes alarms by process and impact severity, facilitating targeted interventions.
The benefits of the Paul Wurth PCIXpert system include sustained operational efficiency, reduced costs, and enhanced decision-making capabilities for plant operators. By providing an easily accessible web-based service, it ensures that critical performance data is readily available to stakeholders, supporting continuous process optimization and contributing to the long-term success of PCI operations.

KEYWORDS: PULVERIZED COAL INJECTION – PROCESS MONITORING – DIGITAL TWIN – INDUSTRY 4.0 – ALARM MANAGEMENT

INTRODUCTION:

Pulverized Coal Injection (PCI) is a pivotal technology in the steelmaking industry, primarily utilized to enhance the economic and environmental efficiency of blast furnaces. By injecting pulverized coal into the furnace, PCI allows the substitution of expensive coke with a more cost-effective reducing agent, namely coal. This substitution not only reduces operational costs but also contributes to a significant decrease in carbon dioxide (CO2) emissions, as it lowers the carbon input required per ton of produced hot metal.
To maximize these benefits, PCI plants must maintain high availability and reliability. Further ensuring a consistent and precise global coal flow control, along with very accurate distribution of coal onto the single tuyeres, is essential to maximize the coal combustion efficiency, allowing for increased coal injection rates. Additionally, utility consumptions must be kept close to design calculations to optimize resource utilization and increase efficiency.
Achieving these operational goals requires robust monitoring and management systems that can handle the complexity of PCI installations. Paul Wurth PCIXpert is designed to address these needs by providing comprehensive monitoring capabilities that enhance plant efficiency and reliability. This paper explores how PCIXpert facilitates the optimization of PCI operation, ensuring both economic and environmental objectives are met.

PCIXPERT: A PROCESS MONITORING TOOL

Pulverized Coal Injection (PCI) plants are inherently complex installations, characterized by their intricate process-oriented operations, necessary for the pneumatic transport of pulverized coal with fluctuating conveying behaviour. They generate a substantial amount of process information, which must be effectively correlated to derive meaningful insights and results analysis. Through the long-term experience gained by execution of various PCI operational audits at our customers worldwide, it has become evident that in most PCI plants, small deviations in PCI processes accumulate over time, leading to significant operational challenges. These include process instability, decreased injection performance and availability, as well as increased nitrogen consumption—a common yet suboptimal solution to maintain operational continuity.
These observations highlight the need for an advanced monitoring tool capable of continuously supervising PCI plant operations, similar to the expertise offered by SMS group specialists in Luxembourg during their on-site optimization audits. Paul Wurth PCIXpert was developed to fulfil this need, offering a comprehensive solution that mirrors the analytical capabilities of experienced personnel, thereby ensuring sustained performance optimization.

Key Features and Functionalities

1. ***Continuous Performance Evaluation***: PCIXpert provides detailed analysis of plant performance over various time periods, including the last shift, day, week, or month. While real-time monitoring is available, its primary purpose is to analyse and monitor performance trends, offering insights that are not typically available through the customer's existing systems. Key performance indicators (KPIs) are utilized to provide a detailed overview of plant operation status, allowing for an easy identification of any deviations from optimal operation conditions.

2. ***Result Oriented Approach***: Through the use of key process indicators, PCIXpert delivers direct results analysis that requires no further interpretation by the customer. This approach streamlines decision-making and saves time, allowing operation and process managers to focus on implementing necessary improvements efficiently.

3. ***Smart Alarm Analysis***: The system incorporates an advanced alarm management tool that categorizes alarms based on process and impact severity. This approach enables users to prioritize interventions effectively, ensuring that limited resources—often stretched due to multiple tasks—are allocated to address the most critical issues impacting plant stability. Further, the clustering of alarms by process allows for much faster failure analysis with deeper insights compared to the analysis in the existing level 1 alarm system.

4. ***Results Visualization***: The monitoring tool operates as a web-based application, built on a customized version of Grafana. Results are visualized through industrial dashboards, which facilitate the assessment of plant performance and support informed decision-making to optimize operations.

Objectives and Benefits

- ***Enhanced Operational Efficiency***: By providing detailed insights into PCI processes, PCIXpert helps operators maintain global flow and distribution accuracy close to design specifications, ensuring high operational efficiency and improved coal combustion behaviour.
- ***Improved Reliability***: The tool enhances the reliability of PCI plants by early detection of potential issues, reducing downtime, and increasing plant availability.
- ***Cost Reduction***: Optimized resource utilization, namely maintenance staff, and reduced utility consumption lead to significant cost savings for PCI operations.

PCIXpert introduces an innovative approach to managing PCI plants by integrating advanced monitoring technologies with industry-specific expertise. This robust solution is designed to meet the economic and environmental challenges of modern steelmaking, leveraging the capabilities of Industry 4.0. Functioning as a Digital Twin of the PCI plant, PCIXpert incorporates the plant's specific process design knowledge at any

operational point, enabling precise KPI monitoring by comparing actual operations with established baselines.

Fig.1 – PCIXpert Overview

DATA MANAGEMENT AND ANALYSIS FRAMEWORK

To develop the PCIXpert, it is essential to systematically collect data from various processes within the PCI plants. These data are gathered and stored in a dedicated database, ensuring robust data management and accessibility. Following collection, the data undergo processing within a specialized tool that applies industry-specific expertise to generate insightful results. These processed results are then returned to the database and made available to end users through BIXpert, a customized version of Grafana, facilitating comprehensive visualization and analysis.

Data Collection and Storage

PCIXpert collects critical data from various levels of the customer's PCI plant operations. This includes:

- **Level 1 Data**: Fundamental process parameters such as pressures and flows, which provide real-time insights into the operational state of the plant
- **Level 2 Data**: Calculated results such as coal flow and set points, which offer a deeper understanding of process control and operational habits.

The collected data is stored in a robust time series database, with Apis from Prediktor serving as the standard platform. This database ensures data integrity and accessibility over extended periods, up to several years, enabling performance comparisons and trend analyses over time. This long-term storage capability is crucial for identifying patterns, assessing improvements, and driving continuous optimization of PCI operations.

Data Processing

RulesXpert is a versatile platform that empowers domain experts to automate their process knowledge and maintenance expertise through rule-based logic. With its user-friendly, zero-code interface, RulesXpert allows for the creation, testing, and execution of complex control schemes and process monitoring without the need for conventional coding skills. It facilitates rapid development of Level 2 functionalities, supporting continuous improvement and market competitiveness by integrating mathematical calculations, recommendations,

alarms, historical data reasoning, and machine learning modules.

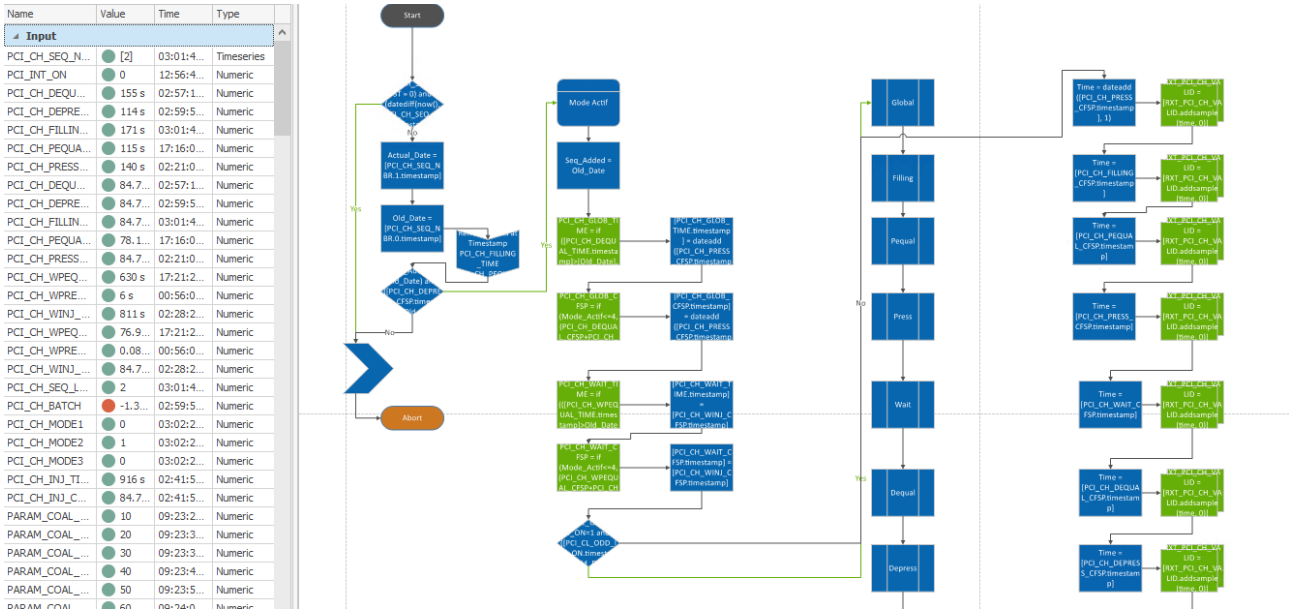

Fig.2 – RulesXpert Interface

When processing data in PCIXpert, careful attention is given to generating new insights rather than replicating existing information already available to operational, maintenance, or process personnel at Level 1 system. The goal is to produce actionable information that guides targeted decision-making to enhance the injection process. Central to this process are the Key Performance Indicators (KPIs), which are calculated and defined within RulesXpert. These KPIs provide a comprehensive assessment of how efficiently the PCI plant is performing across various processes. For example, the availability KPI evaluates the plant's responsiveness to the blast furnace's coal injection demand. It monitors the number and duration of stops and interruptions, differentiating between those caused by external factors, such as operator interventions, and those resulting from internal process failures. This nuanced analysis enables maintenance and process engineers to identify root causes and implement corrective actions swiftly, thereby enhancing plant reliability and efficiency.

By focusing on these KPIs, PCIXpert ensures that users have access to insightful metrics that facilitate continuous improvement and strategic decision-making, ultimately driving operational excellence in PCI plants.

Visualization

The results of data processing from PCI plants are presented through BIXpert, a dashboard software tailored for industrial processes. BIXpert is a modified version of Grafana open-source software, enhanced with proprietary "Xpert"-plugins developed by Paul Wurth for industry-specific use cases. These plugins facilitate interactive data selections, integrate industrial plant hierarchies, and provide industry-specific visualizations without requiring coding skills. BIXpert aims to deliver a powerful, modern, and user-friendly data visualization tool, enabling process experts to build real-time, web-based dashboards and applications effortlessly.

BIXpert supports multiple user connections, allowing collaborative access to dashboards. It also offers features such as multi-language support and customizable time zones, ensuring that visualizations are aligned with the customer's location and preferences. Additionally, users can select the time range for results visualization. By default, the time range for displaying data in BIXpert is set to the last finished shift, ensuring users have

immediate access to the most recent performance results. However, this time range is fully adjustable, allowing users to navigate through shifts, days, weeks, or months. This flexibility enables users to analyse performance trends over various periods, adapting the visualization to their specific needs. This adaptability enhances user experience and facilitates effective data-driven decision-making across diverse industrial settings.

Beyond the Overview dashboard, which functions as the main landing page, PCIXpert provides in-depth insights into specific PCI plant processes through a set of dedicated dashboards. A navigation panel allows users to move effortlessly between these dashboards, facilitating comprehensive analysis and monitoring through the strategic use of Key Performance Indicators (KPIs).

Fig.3 – Navigation Panel

DASHBOARDS OVERVIEW

The PCIXpert system is composed of five distinct dashboards, each providing unique insights into various processes of the PCI plant:

- **Overview**: This dashboard encompasses all processes within the PCI plant, treating each process individually in dedicated panels. It is designed to offer a global perspective on the plant status, utilizing a top-down approach. It starts with general information such as plant availability and injection rates and progresses to more detailed data like deviations and distribution accuracy.

- **Process**: Focused on the conveying hoppers, this dashboard provides detailed information about all sub-sequences performed by the injection vessels, offering insights into the intricacies of the injection process.

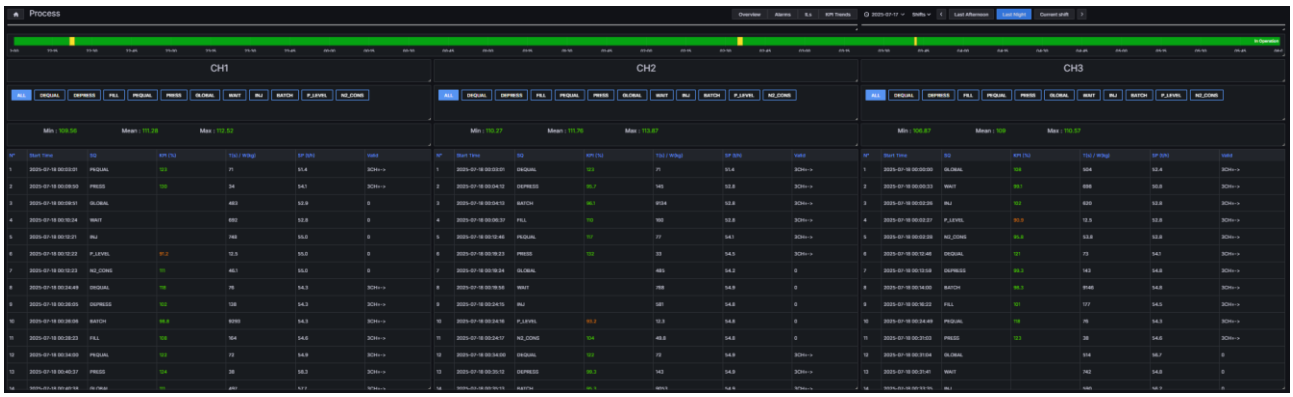

Fig.4 – Process Dashboard

- **Alarms:** This dashboard delivers detailed information about alarms related to the PCI plant, including the processes impacted, the frequency and timing of occurrences. Further it allows an efficient search and sorting of alarms based on their impact severity as well as on the process they belong to. It aids in prioritizing interventions and resource allocation, as well as in an effective failure analysis.

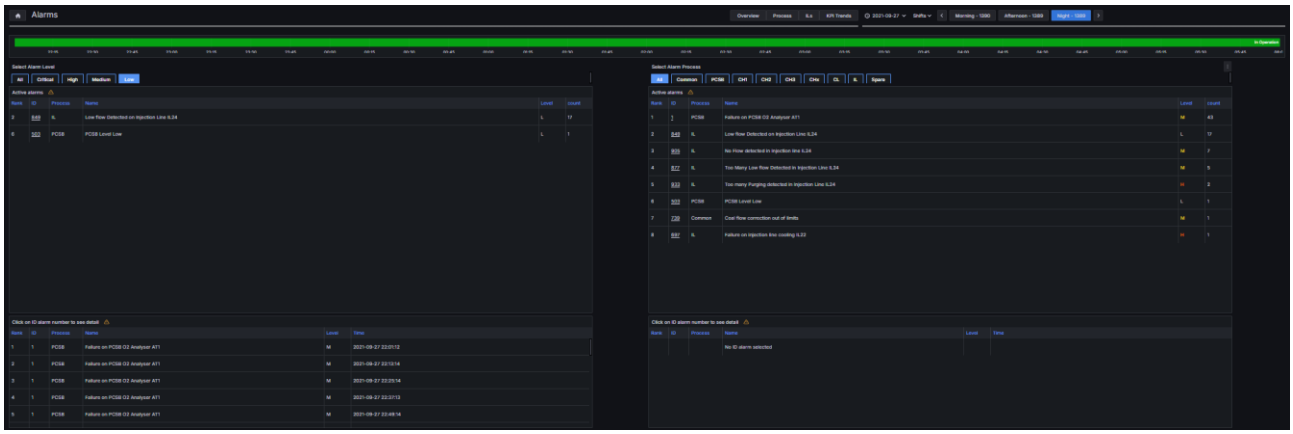

Fig.5 – Alarms Dashboard

- **Injection Lines:** Dedicated to the injection lines, this dashboard showcases each line within the plant, providing relevant information such as the number of stops, interruptions, process conditions like flow rates and control behaviour, facilitating detailed analysis of operational efficiency.

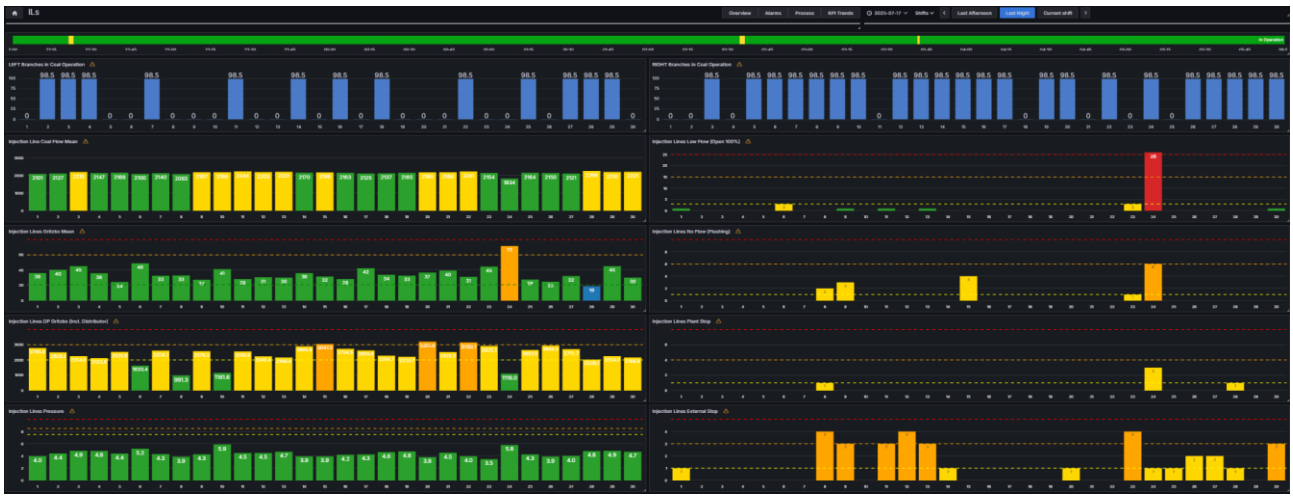

Fig.6 – Injection Lines Dashboard

- **KPI Trends:** Defaulting to a one-month view, this dashboard is designed to study the evolution of the KPIs displayed in the Overview over extended periods. It supports strategic planning and decision-making for future operations.

Fig.7 – KPI Trends Dashboard

CONCLUSION

Paul Wurth PCIXpert system represents a significant advancement in PCI plant management, offering comprehensive monitoring and analysis capabilities that enhance operational efficiency and reliability. By integrating innovative tools like BIXpert for data visualization and RulesXpert for data processing, PCIXpert empowers users with actionable insights and facilitates informed decision-making. The system's multi-dashboard approach provides detailed perspectives on various plant processes, ensuring that users can effectively monitor and optimize performance.

Through its strategic use of Key Performance Indicators (KPIs), PCIXpert delivers valuable metrics that guide maintenance and process engineers in achieving sustained improvements. As the industry continues to face challenges related to resource utilization and process optimization, PCIXpert stands out as a vital tool for fostering competitiveness and ensuring safe operations.

The deployment of PCIXpert across multiple PCI locations has already demonstrated its potential to improve plant availability and utility consumption, underscoring its role in driving long-term success in PCI operations. By providing users with a robust, web-based service, PCIXpert ensures that critical performance data is readily accessible, supporting continuous process optimization and contributing to the enduring success of PCI operations.

Digitalization of Material Properties Across the Entire Process Chain

Uwe Diekmann*, Marco Thomä*, Yingyan Yu*

***Matplus GmbH, Hofaue 55, 42103 Wuppertal, Germany:**

Steel and metal-intensive industries are advancing digitalization beyond traditional ERP, PLM, and MES systems to more effectively integrate materials technology and manufacturing processes within enterprise IT environments. This paper presents a materials management system based on a scalable JSON data structure that consolidates test data, process histories, CAE model libraries, and decision workflows. A central feature is a semantic knowledge graph that links material properties with process data across the entire production chain. This integrated approach enables faster product development, improved process control, and supports downstream applications such as Wire and Arc Additive Manufacturing (WAAM).

KEYWORDS: DIGITALIZATION, MATERIALS DATABASES, STEEL INDUSTRY, MATERIAL PROPERTIES, PROCESS HISTORY, KNOWLEDGE GRAPH, CAE, WAAM

Funding support from the “Ministerium für Wirtschaft, Innovation, Digitalisierung und Energie des Landes Nordrhein-Westfalen” and collaboration with HEGGEMANN AG and verlinked GmbH enables practical applications in aerospace, notably within the “Digitale Fabrik” and “Digitale Aerospace Fabrik” initiatives parented by Matplus GmbH.

INTRODUCTION

Digitalization in the steel industry requires a comprehensive framework that integrates material behavior, production processes, and end-to-end traceability. This next phase of digital evolution focuses on capturing dynamic material states across the full manufacturing chain, including advanced downstream processes such as Wire and Arc Additive Manufacturing (WAAM). Strategic knowledge management is critical for preserving operational expertise and accelerating the onboarding of new personnel. Reliable decision-making depends on access to structured knowledge from past projects, including test data and process records. Linking this information with material master data via integrated reference databases enables effective knowledge reuse. By combining materials engineering with digital infrastructure, this approach enables precise control of material properties throughout the entire process chain. It optimizes factors such as alloy design and energy use, improving efficiency and supporting the rapid development of innovations like green steel production.

Matplus EDA® provides a practical infrastructure with a scalable database, microservices, mathematical functions, and flexible visualization tools in multi-user environments (1). It is used across various industrial companies as a central platform for materials engineering, from modeling and data analysis to decision support. This paper shows the digitalization of material properties across the entire process chain, including downstream processes like Wire and Arc Additive Manufacturing

(WAAM) and ooperations such as heat treatment and machining, based on findings from the publicly funded DAF (Digital Aerospace Factory) project.

1. Digital Material Infrastructure

The EDA® infrastructure consist of a JSON backed database, a Python based middleware and a web frontend based on FOSS (free and open source software) technologies. It integrates and harmonizes various data sources and tools, including:

- **Reference Databases:** The system consolidates key material databases, including Stahldat SX® for steels and polymers, and can be extended with sources like MMPDS for aerospace (2,3). These serve as a foundation for company-specific material data management, linking upstream inputs with downstream decision-making to enhance traceability and technical reliability.
- **Materials Selection and Assignment:** Material data and material cards provide a consolidated single source of truth for materials information. A streamlined app supports downstream applications such as CAE, and enables efficient material selection and assignment during product development through a lean and intuitive interface.
- **Lab and In-line Test Data:** Incorporates standardized formats such as SEP 1240, VDA 239-301, DIN SPEC 9012 ensuring that test data is systematically captured and utilized.
- **Knowledge Graphs:** Display the evolution of materials properties along complete manufacturing routes with several process steps in a comprehensive way.
- **CAE Model Libraries:** Supports a range of material models like Johnson-Cook and Ramberg-Osgood, facilitating comprehensive simulations and analyses-
- **Seamless CAE Integration with Python Tools:** Utilizes Python-based tools such as SciPy and PyLife for advanced data analysis and fatigue evaluation, enhancing the system's analytical capabilities

This digital infrastructure supports advanced material and process optimization across all stages of product development and manufacturing. A key capability is the end-to-end tracking and management of material property evolution throughout the process chain. This includes linking process parameters with material models to predict behavior and performance. The approach was demonstrated in the Digitale Aerospace Fabrik research project, where it was applied to a steel component manufactured via WAAM, followed by heat treatment and machining. The effectiveness in a practical application could be demonstrated regarding microstructural analysis, and integrated modelling for technology development.

2. Process Flow Analysis

To systematically represent end-to-end manufacturing and the evolution of material properties within the materials management system, a knowledge graph based on a Directed Flow Graph architecture was adopted. This framework models each manufacturing process as a node, with directed edges capturing relevant process data like temperature-time-series as well as the evolution of material properties between these processes. The approach emphasizes process-centric representation, flow conservation, and graph extensibility (4).

A visual process modeling environment supports structured modeling and interactive configuration of complex flows within manufacturing processes. The system features a modular interface with five core GUI components: Tree Browser, Workspace, Tool bar, Nav Bar and Popup forms. This architecture enables high interactivity and maintains modeling efficiency for engineering users. The modeler allows intuitive model construction via a drag-and-drop interface without requiring programming expertise.

The system uses JSON objects as the core data structure, enabling standardized serialization, storage, and transmission. Each graph model can be exported as a JSON file compatible with back-end databases such as MongoDB or used as input for downstream computation modules. The data scheme supports nested structures and extensible attributes, enabling high-dimensional process representation. The editor features strong extensibility and responsive design, supporting multi-material flows, branching process paths, and multi-layer modeling, making it suitable for complex scenarios like additive manufacturing and distributed production.

Fig. 1 shows the downstream process chain for manufacturing a part via WAAM, heat treatment, and machining.

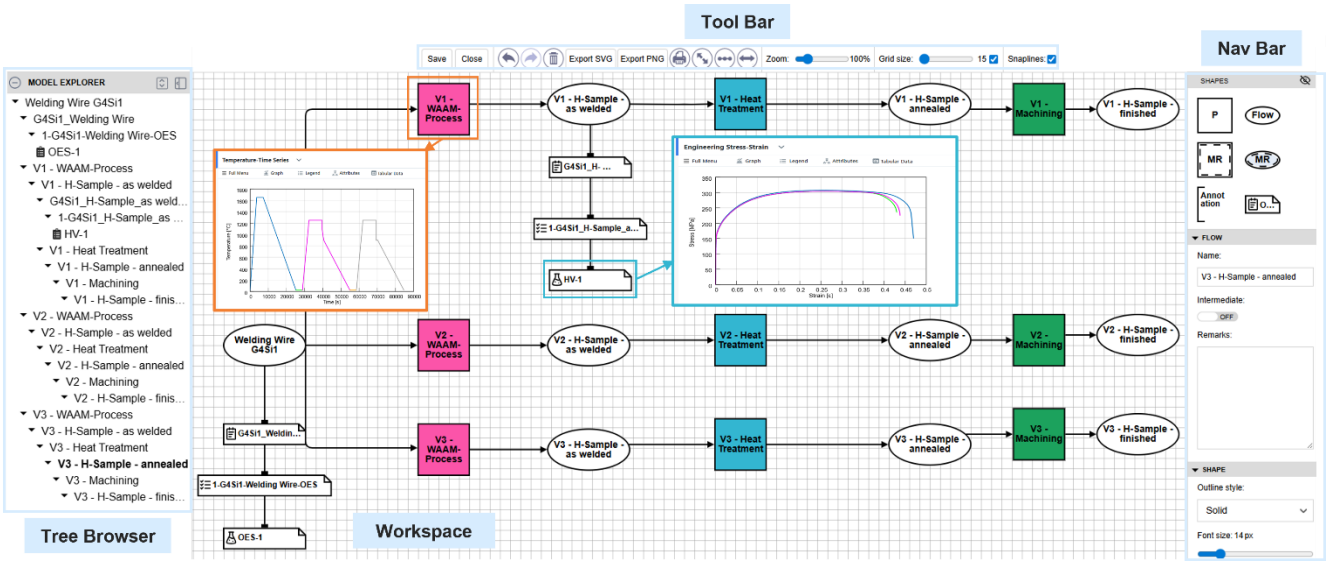

Fig. 1- Graphical Process-Flow-Analysis modeler integrated in EDA® showcasing evolution of materials properties of a WAAM manufacturing route with process data (orange) and test data (blue)

Processes are displayed as colored squares, ellipses represent material conditions and rectangles were used for test date in the format of a work-break-down-structure (order, batch, test). This semantic linking combines process data (example orange box) and material testing (example blue box) for accurate analysis and precise predictions and also simplifies modeling with the intuitive modeler including a seamless data import via flexible importers.

3. Exploratory Data Analysis

Exploratory Data Analysis (EDA®) plays a central role in transforming raw process and material data into actionable insights. To support this, the digital infrastructure enables the creation of aggregation tables that consolidate selected data points from process flows and the underlying knowledge graph. These tables serve as a structured basis for targeted analyses across the entire process chain. Graphical exploration tools allow users to visualize trends, correlations, and anomalies in material behavior, while integrated curve-fitting functions support the identification and parametrization of relevant material models.

A practical example originating from the DAF project includes data from materials simulation using JMatPro®, where thermo-physical and phase transformation properties are aggregated to assess their impact on downstream processes (Fig. 2). Visual analysis and curve fitting help identify trends across alloy compositions and support model calibration for CAE and process optimization.

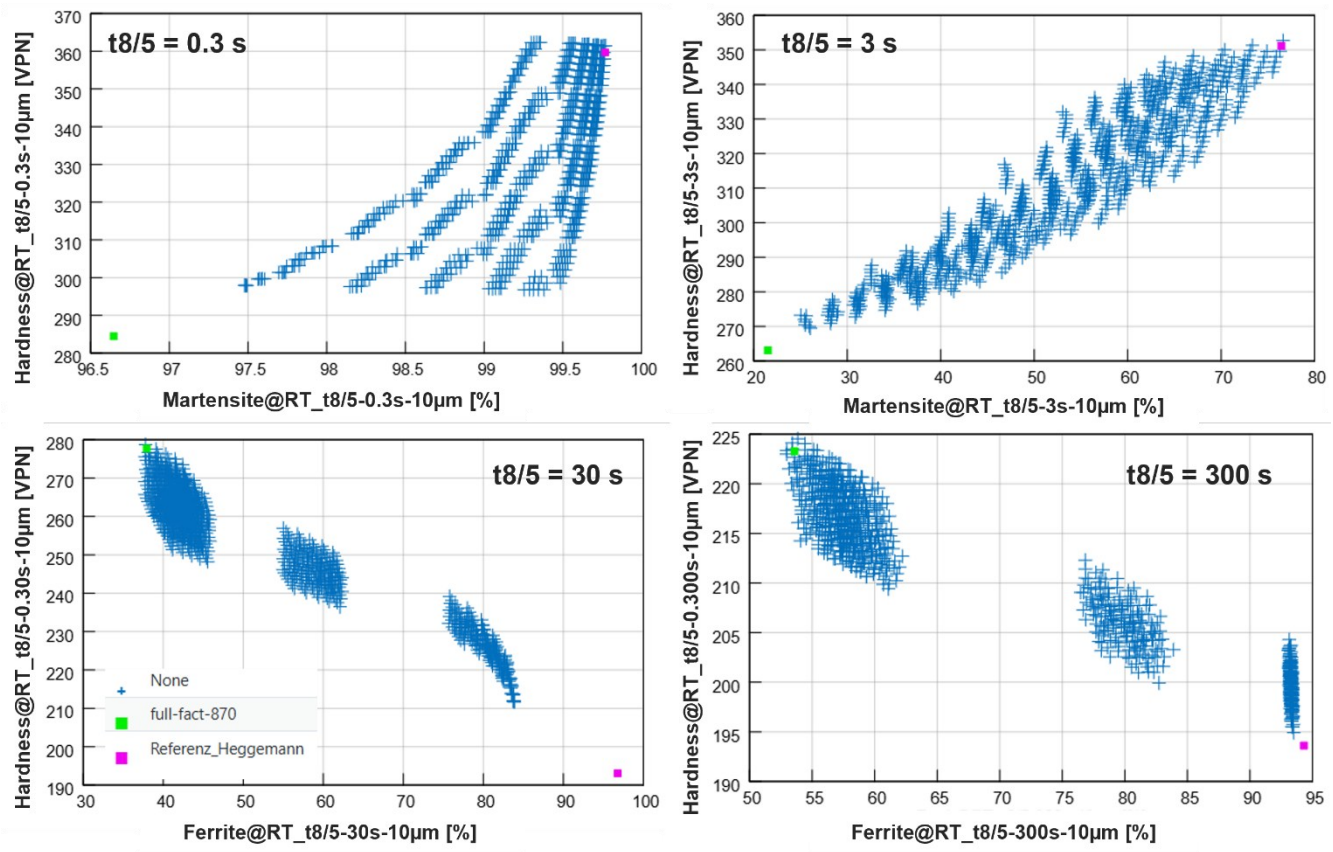

Fig. 2 - Overview of hardness results from JMatPro® calculations over microstructure proportions depending on t8/5 times: upper row martensite, lower row ferrite

The figure shows the simulated impact of different cooling rates on the microstructure and resulting hardness of the welding wire material G4Si1 for a full-factorial design of experiment.

4. Material Card Generation

The materials management system supports the entire workflow from test data evaluation to system-neutral CAE material cards (1,5,6). It is built on three pillars:

- **Harmonized Data Structure:** JSON-data format is used to link material models to master data and lab results, ensuring compatibility across systems.

- **Infrastructure for Scientific Tasks:** Stores and parametrizes constitutive equations, supports curve fitting, and integrates Python tools for advanced analysis. It also incorporates external FOSS libraries for extended functionalities.

- **Import/Export Functions:** Facilitates flexible import/export of material cards between systems, consolidates cards from various platforms, and provides internal visualizations for comparisons.

This approach improves traceability, efficiency, and data security across diverse CAE environments.

5. Workflow Automation

To simplify operations and improve traceabilty, the materials management system includes an integrated workflow editor and engine based on BPMN 2.0 (Business Process Model and Notation) and DMN (Decision Model and Notation). These workflows coordinate tasks across departments with notification features and automated plugins, ensuring end-to-end traceability and standardization. By aligning with BPMN and DMN, they reduce implementation and operational costs through lean, efficient execution. In the DAF project, several such workflows were deployed, including one for automated weld seam inspection, as shown in Fig. 2.

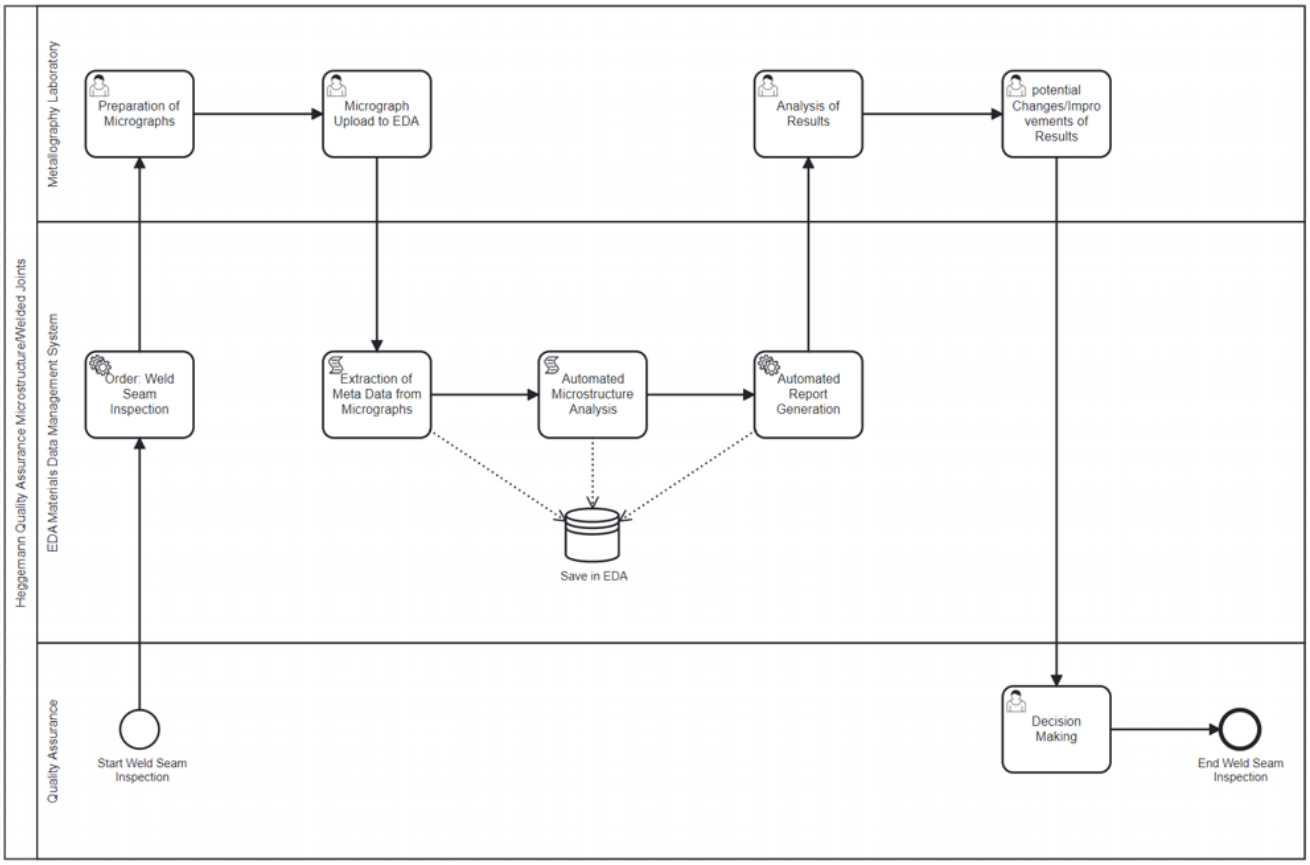

Fig. 3 - Electronic workflow for the inspection of weld seams from the DAF project

The workflow spans three lanes: quality assurance, the materials management system, and the metallographic lab. Quality assurance initiates the weld seam inspection and makes the final decision. The materials management system automatically generates the inspection order, runs the microstructure analysis, and provides a report. The lab prepares micrographs, uploads them to the system, and reviews the auto-generated report with the option to adjust or refine the analysis manually.

6. Conclusion:

Digitalization is essential for advancing materials engineering and optimizing processes across the steel industry. A unified infrastructure that integrates material behavior, process history, and traceability provides a scalable, standards-compliant foundation to address technological and workforce challenges. At its core is a graph-based architecture that enables end-to-end tracking of material property evolution, enhanced by visual modeling tools, automated workflows, and CAE-ready material cards. Demonstrated through the manufacturing of a WAAM-produced steel component, including heat treatment and machining, the system supports data-driven decisions, accelerates innovation, and ensures consistency across the entire value chain.

ACKNOWLEDGEMENTS

Funded by: Ministerium für Wirtschaft, Innovation, Digitalisierung und Energie des Landes Nordrhein-Westfalen
Collaborators: HEGGEMANN AG, verlinked GmbH, Matplus GmbH

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TOWARDS A STANDARDIZED DIGITAL PRODUCT PASS FOR GREEN STEEL: DEVELOPING NOVEL FRAMEWORK WITH REAL-TIME CO_2 TRACKING AND SECURE DATA CONNECTIVITY FOR ESPR COMPLIANCE

Doruk Sahinel, Carsten Stöcker, Ricky Thiermann, Johannes Ebert – Spherity GmbH, Germany
Joachim Denker – ASINCO GmbH, Germany
Andre Weber – Mannstaedt GmbH Germany

Transformation towards climate-neutral production in the metal industry requires innovative solutions for tracking greenhouse gas emissions. While major steel manufacturers are already exploring digital product passports (DPP) as part of their sustainability strategies, small and medium-sized enterprises (SMEs) in the metal processing industry often lack standardized methods for quantifying emissions.
This paper introduces a DPP architecture for SMEs in metal processing, integrating edge-computing to dynamically assess the CO_2 footprint of products. Unlike conventional static product information systems, the proposed approach enables real-time tracking of energy consumption with model-based digital twins. This solution aims at sustainability reporting across the supply chain, with interfaces and access control mechanisms to address privacy concerns of SMEs during data exchange. The architecture leverages industry-compatible interfaces for data exchange with Enterprise Resource Planning (ERP) systems and regulatory platforms, ensuring compliance with the Ecodesign for Sustainable Products Regulation (ESPR). Pilot projects in a real-world hot rolling mill and foundry validate the system's ability to enhance transparency and energy efficiency with real-time emission monitoring. By integrating dynamic energy monitoring into the green steel DPP framework, this research presents a pathway toward standardized and verifiable CO_2 assessment in metal processing. The findings intend to contribute to ongoing EU standardization efforts.

KEYWORDS: DIGITAL PRODUCT PASS – CO_2 FOOTPRINT – EDGE COMPUTING – ENERGY MONITORING – METAL PROCESSING – SUSTAINABILITY – DIGITAL TWINS

INTRODUCTION

The iron and steel industry are among the largest emitters of carbon dioxide (CO_2). According to World Steel Association [1], the global steel industry emitted an average of 1.891 tonnes of CO_2 per tonne of steel produced in 2020. With a total production volume of 1,860 million tonnes, this sector's direct CO_2 emissions amounted to approximately 2.6 billion tonnes, accounting for 7% to 9% of global CO_2 emissions. To achieve climate neutrality by 2050, appropriate and innovative solutions are essential to transition current processes to low-carbon production. DPP stands out as a key enabler to support this transition, offering a structured approach to track product-specific emissions across the supply chain, and supporting the transformation towards more transparent, data-driven decarbonization strategies in the steel industry. An important addition to this fact in the EU is that according to the Ecodesign for Sustainable Products Regulation (ESPR) [2], all intermediate products made of iron, steel, and non-ferrous metals in the EU must be equipped with a DPP in the future. Article 18 of the regulation states that iron and steel are prioritized product groups and hence shall be part of the first working plan, which shall be adopted by 19 April 2025.

While major steel manufacturers are already exploring DPP as part of their sustainability strategies, small and medium-sized enterprises (SMEs) in the metal processing industry often lack standardized methods for quantifying emissions. To overcome this digital divide, our main motivation in this study is to provide a DPP approach that is inclusive and specifically tailored to SMEs. By developing a green steel DPP framework that meets future standardization, regulatory and certification requirements, this study provides an early-stage solution that aligns with upcoming industry and legislative needs. This ensures a more precise, verifiable, and scalable solution for sustainability reporting across the supply chain, with necessary interfaces and access

control mechanisms to address privacy concerns of SMEs during product-related data exchange. The effectiveness of the solution is also demonstrated over pilot projects in a real-world hot rolling mill and foundry. The goal of this study is to develop a system that enables continuous data collection for DPPs of various products produced in legacy systems, exemplified by selected segments of the metal processing supply chain, specifically in foundries and hot rolling mills, to support the development of DPP standards. This requires comprehensive metrological tracking of material flows, complete sensor-based acquisition of all relevant measurements, and the modeling of product-specific greenhouse gas emissions. An innovative aspect is the development and implementation of measurement technology that fully captures material flow in discontinuous production processes. The real-time recording of energy consumption during production requires that digital twins of the products simultaneously evaluate measurement data at each production stage. These twins capture information on the physical properties, energy balance, and performance of the physical products. The concept of this study and the key building blocks are visualized in Fig. 1.

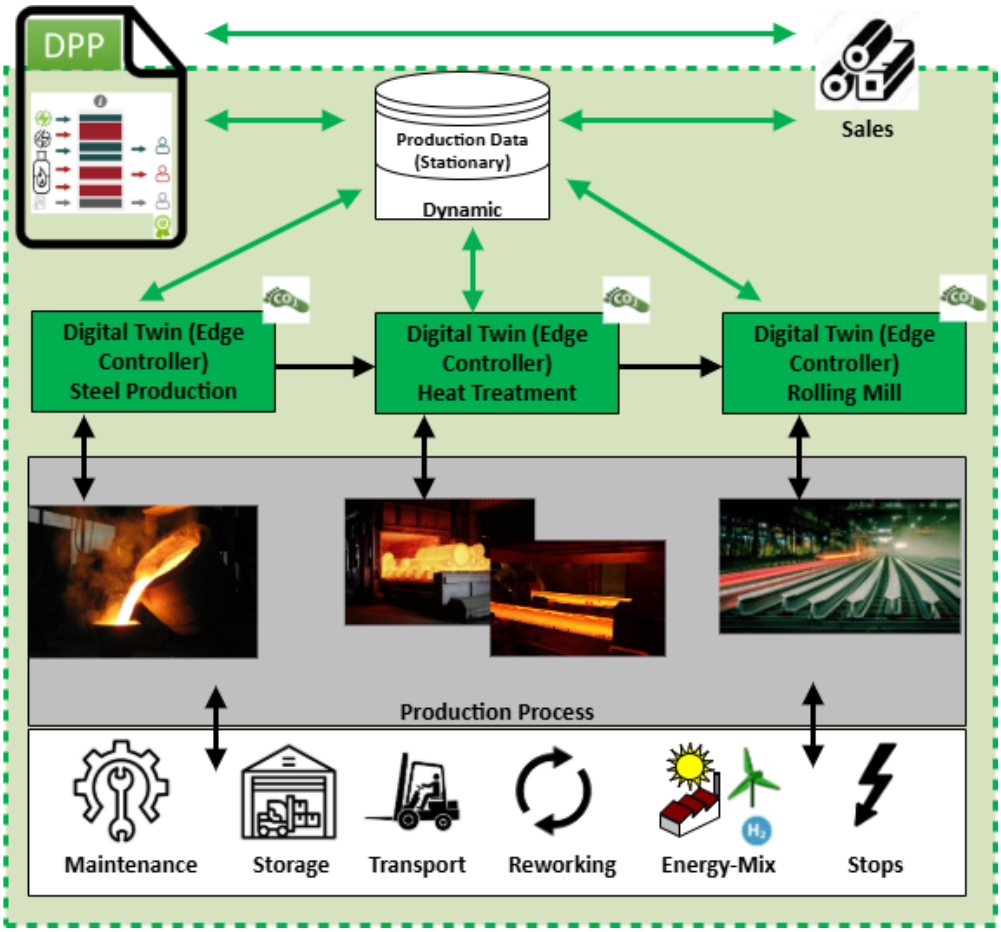

Fig.1 - Concept of Real-Time Energy Data Acquisition and DPP Generation Using the Example of a Rolling Mill

The rest of the paper is structured as follows: Section 2 analyzes the regulatory context and reviews existing DPP initiatives, highlighting gaps and challenges relevant to our approach. In Section 3, our innovative Green Steel DPP approach is explained together with relevant DPP data models and the handling of non-stationary variables in industrial environments. In Section 4, a case study is outlined based on pilot implementations in a hot rolling mill and a foundry. The integration of DPP APIs, middleware for energy and process monitoring, and access to legacy manufacturing databases is demonstrated with a pilot project. The paper is concluded in Section 5.

BACKGROUND

In alignment with the Paris Agreement, the European Union (EU) has established ambitious climate and energy objectives, aiming to achieve a net-zero greenhouse gas emissions target by 2050. The EU Green Deal [3] emphasizes critical strategies, including energy and resource-efficient building renovations, a zero-pollution ambition for a toxic-free environment, and, most importantly, the mobilization of industries to foster a clean and circular economy. The development of DPPs is strongly influenced by EU regulatory initiatives that promote environmental sustainability, as DPP is foreseen as an integral part of a comprehensive sustainability strategy. According to Plattform Industrie 4.0 [4], the DPP is a central element of the European circular economy strategy in the coming years across various sectors, including the steel industry.

As mentioned in Section 1, ESPR (2024/1781) is a cornerstone of the European Union's strategy to enhance the environmental performance of products throughout their lifecycle [5]. It introduces a series of regulatory measures aimed at promoting sustainability in product design, use, and end-of-life management. Central to the regulation are the eco-design requirements (§5), which are further specified through performance requirements (§6), information requirements (§7), and the introduction of the Digital Product Passport (§9) [6]. ESPR covers the essential requirements that a DPP shall comply and requires that products may only be placed on the market or put into service if a DPP is available in accordance with delegated acts to be adopted under the future Regulation. Based on the list in Article 5 of the ESPR [5], this study mainly aims ESPR compliance with the following requirements:

1. Energy use and energy efficiency: A core focus of the paper is real-time tracking and optimization of energy consumption and CO_2 emissions during manufacturing processes.
2. Resource use and resource efficiency: By providing new transparency regarding product-specific energy and resource usage, the study contributes to the development of innovative production processes with more efficient resource use.
3. Environmental impacts: The primary goal of the paper is to assess and reduce the carbon footprint through digital tracking and verifiable reporting

Concerning the global impact of DPPs, the UN Transparency Protocol (UNTP) is an initiative developed by UN/CEFACT to support the digital transformation on an international level and to ensure transparency in global trade processes [7]. As a fundamental framework, it emphasizes the importance of data standardization and interoperability to enable seamless information exchange across industries and regions. The UN Transparency Protocol (UNTP) for Digital Product Passports is expected to be officially launched in 2025 as UNECE Recommendation No. 49. Pilot tests are currently being conducted, and UNECE is working on finalizing the recommendation. These recent developments highlight the relevance this study and confirm the need to develop standardized and interoperable solutions for DPPs in the steel industry at an early stage and in parallel with emerging regulations.

As seen from the regulatory framework, the introduction of the Digital Product Passport is gaining increasing importance both in European industry and globally. Building on these regulatory foundations, several significant European and industry-led initiatives have emerged to implement the DPP concept. CIRPASS [8], a key EU-funded project, aims to develop interoperable DPP architectures that align with ESPR requirements across various value chains. Though primarily focused on electronics, batteries, and textiles, CIRPASS explicitly includes iron and steel as a priority product group for future delegated acts under the Ecodesign for Sustainable Products Regulation. However, CIRPASS primarily focuses on digital event histories and metadata standards, lacking mechanisms to link the intrinsic physical properties of materials to their digital records.

Since the battery sector will be the first in the EU to adopt mandatory DPPs starting in February 2027 [9], the Battery Pass project [10] serves as a pioneering use case that can inform and guide other industries. The project outlines a comprehensive DPP architecture for the battery sector, built on standardized technical components—including shared data models and unique product identifiers—and implemented through a multi-tiered system that combines central EU services with decentralized, industry-operated components. This

architecture is intended as a general blueprint for DPPs across different sectors, meaning that despite the differences between batteries and steel products, the results can be transferred to the steel sector. Regarding key industrial stakeholders in Germany, a white paper on DPPs titled A Circular Platform for Used EV Batteries in Europe was published [11]. The paper describes the role of Digital Product Passports, particularly the European Digital Battery Passport, which assigns each battery a unique digital identity and tracks performance, carbon footprint, and compliance with sustainability regulations.

In the steel industry, various initiatives and projects are currently underway to develop and implement digital product passports or similar concepts, but these efforts remain insufficient in their current form. For instance, [12] describes the development of a cloud-based digital solution designed to address the need for tracking the provenance of products, particularly reinforcing steel in the construction industry. The CARES Cloud platform provides a real-time system that traces every batch of steel from its origin to the construction site, ensuring compliance with safety, quality, and sustainability regulations. The platform uses customizable dashboards, QR codes, and digital passports to track the carbon footprint, material compliance, and product quality, offering a digital twin for each batch. However, the paper does not provide a standardization alignment for DPPs, does not explain the use of decentralized identity management and interoperable verifiable credentials based on standards.

GREEN STEEL DPP

DPPs are comprehensive digital records that provide detailed information about a product's lifecycle, including a steel product's origin, its production processes, and CO_2 footprint, ensuring ESPR compliance and enhancing sustainability reporting. Green steel DPPs, as exemplified in Fig. 2, strive to document a clear and traceable path from the source to the final product, and their implementation of the DPP involves several key implementation steps. Firstly, each steel product batch is assigned a globally unique Decentralized Identifier (DID), enabling cryptographically verifiable traceability from production to downstream applications. A DID is a unique global identifier, which is resolvable with high availability and cryptographically verifiable [13]. W3C DID specification details the framework for decentralized identifiers, including the architecture, data model, and representation of DIDs, and highlights their role in enabling individuals and organizations to create identifiers.

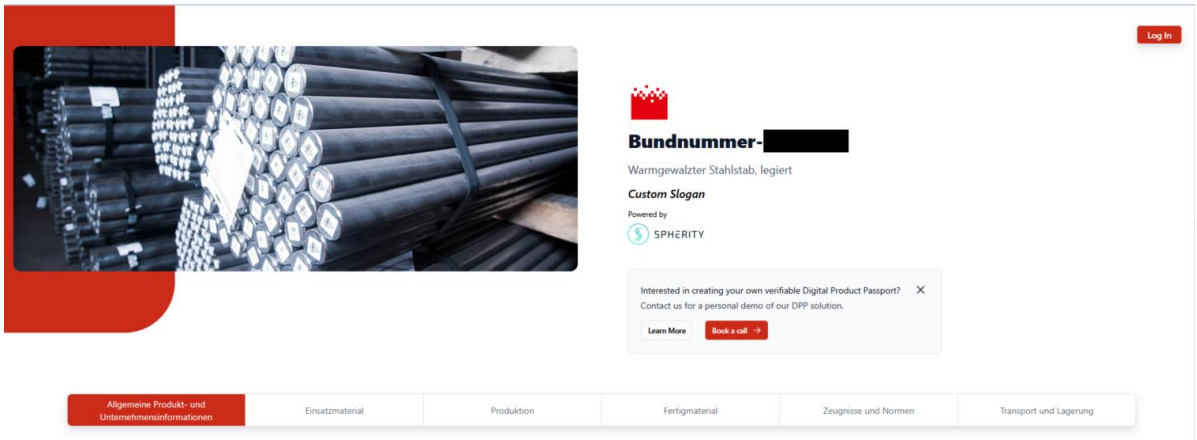

Fig.2 - Green Steel Digital Product Passport Example

The data green steel DPP contains must be made available in a verifiable manner. The data model does not only contain information stored and processed in the ERP systems of the economic operator, but it also contains verifiable data from third parties. For this reason, the responsibilities for data input should be clearly allocated to appropriate stakeholders to prevent information gaps. Third parties and suppliers provide information in the form of open standards like W3C Verifiable Credentials [14], and these credentials are used to verify the company's claims, such as its enterprise identity, environmental and sustainability claims, etc. Verifiable Credentials are tamper-evident credentials whose authorship can be cryptographically verified, allowing them to serve as reliable digital representations of physical credentials. Their use in DPPs enables

legally binding assertions such as certification conformance, ecosystem participation, or material provenance.

To achieve the objectives of the Green Steel DPP, a dedicated data model was first designed to define the semantic structure and data types required for representing steel product information. This model draws on existing standards and initiatives, with alignment to the Catena-X semantic models [15] and mappings to the ECLASS product classification system [16], based on insights from the CIRPASS initiative [8]. Building upon this data model, a sector-specific DPP profile for green steel was developed. This profile specifies which data points are required for documenting the lifecycle, environmental performance, and traceability of steel products. The profile is structured into thematic categories that reflect key lifecycle stages and regulatory requirements, including the following: General product and company information, input materials, production, finished materials, certifications and standards, and transport and storage.

The key data points defined in the green steel DPP profile include:

1. Product identification and characteristics: Information such as the product's name, category, and physical attributes—e.g., dimensions, weight, and condition (e.g., solid steel). This ensures unambiguous identification within the supply chain for the purposes of traceability and verification.
2. Manufacturing details: Data on production sites and production dates that provide transparency in the manufacturing process.
3. Environmental and resource efficiency: Information is provided on material efficiency, energy consumption, water usage, and waste generation during production. This aligns with sustainability goals and the need for DPPs to capture environmental impacts.
4. Performance and durability: Information on mechanical properties such as tensile strength and yield strength, expected service life, corrosion resistance, and wear resistance, to ensure that performance attributes are linked to the product and can be verified throughout its entire lifecycle.
5. Lifecycle information: Includes data on the production date and end-of-life details, which are essential for circular economy applications and to support the reuse or recycling of products.
6. Certifications and standards: The document includes certifications such as recycling strategy, material recycling, and sustainability assessments that confirm the product's compliance with legal standards and verify its environmental and social sustainability.

These elements are designed to enhance traceability, ensure regulatory compliance, and support circular economy goals within the European steel value chain. After all data attributes are filled based on the data model of the DPP, the product identifier (DID) is encoded into a QR code. The QR code provides access to its digital passport, allowing consumers and professionals along the value chain to easily retrieve the product data.

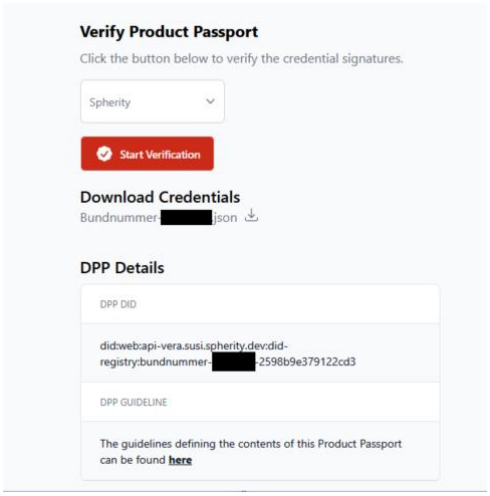

Fig.3 - Verification Interface of the Green Steel Digital Product Passport

As the final step, the Green Steel DPP includes a structured web-based frontend designed for both internal users and external verifiers. The interface provides a login-protected environment for data entry and document management, alongside a verification menu that enables third parties to validate credentials associated with a specific product. Verified users can download machine-readable credentials, inspect lifecycle and emission attributes, and trace certificate-backed sustainability claims. Fig.3 illustrates the verification interface of a Green Steel Digital Product Passport (DPP), where users can authenticate credential signatures and download product-specific data as a JSON file. It also displays the DID assigned to the steel batch. Furthermore, to address access control in decentralized industrial ecosystems, the architecture implements a dynamic rights management system based on Attribute-Based Access Control. Instead of static roles, access permissions are assigned according to contextual attributes. This model allows differentiated access to DPP elements (e.g., full editing rights for product managers or limited certificate upload access for quality officers).

CASE STUDY

To validate the architecture, a case study involving Mannstaedt GmbH's hot rolling mill was conducted. The case study showcases the feasibility of real-time data acquisition, secure integration of product-specific sustainability data, and the dynamic adaptation of new products within legacy industrial environments. Steel company Mannstaedt GmbH operates a complex hot rolling mill, producing approximately 700 distinct steel profile forms. Each profile is characterized by unique product identifiers linked to specific attributes such as dimensions, weight, forming degree, and tooling requirements. Comprehensive data management is crucial due to the extensive variability of product specifications, the necessity to adapt tooling (rollers and fixtures), and varying conditions arising from tool wear.

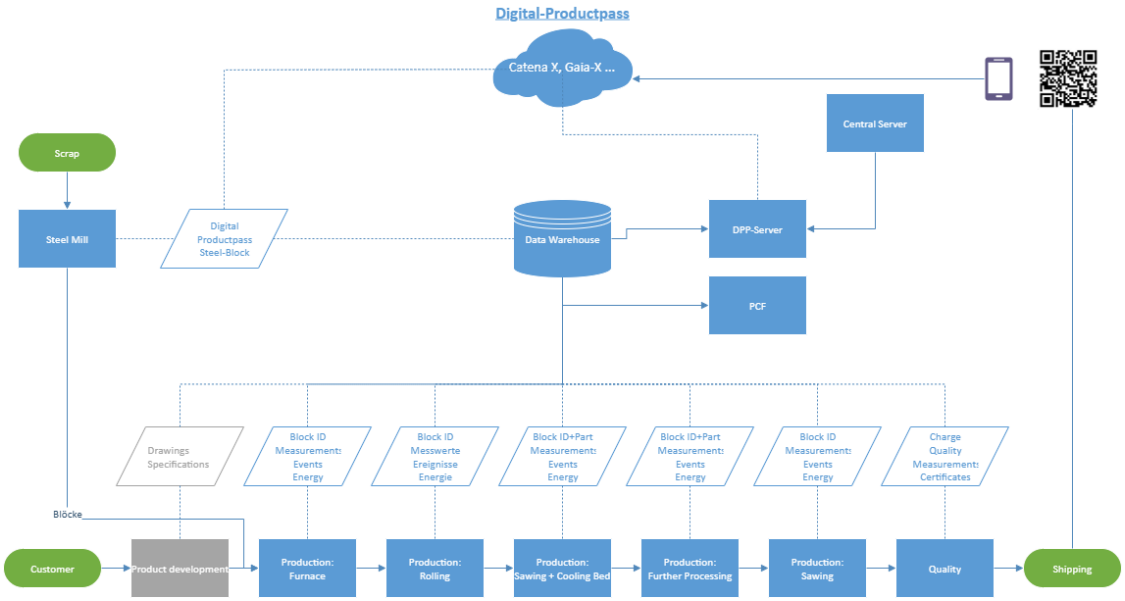

Fig.4 – Integration concept between steel company's data warehouse and the DPP platform.

A pivotal component in this implementation has been the development of a dynamic intelligent interface utilizing Python as the central development environment. This interface operates between the steel company's (Mannstaedt) internal Data Warehouse and DPP service provider's cloud-based DPP platform. Its primary function is to facilitate the seamless and efficient integration of new products into the DPP system. To allow communication between different software systems for DPP generation in an automated way, Application Programming Interfaces (APIs) are used. This process is fully automatable using this Python-based interface that submits structured JSON payloads—based on the predefined steel DPP schema—via API endpoints. Upon successful request validation, a published DPP instance is returned for the steel batch, ready for further population with production-specific data from the manufacturer's internal systems. The integration between

the production database and the DPP platform for automated DPP creation is visualized in Fig. 4.

The proposed middleware architecture utilizes an SQL Server (version 15) Data Warehouse for robust data handling, performing secure and structured data queries and transformations. Data are initially accessed through standardized ODBC/JDBC interfaces, facilitating effective data retrieval from internal enterprise databases. Python-based solutions, leveraging libraries such as pandas, transform SQL queries into JSON or XML formats for seamless integration with external systems. Core to the middleware platform is a dynamic user access management system based on Attribute-Based Access Control (ABAC), which provides fine-grained, flexible permission structures tailored to different user roles, such as product managers, database administrators, security administrators, and compliance officers. This structure ensures secure and role-specific access, supporting the addition and management of new products and their respective critical documents, including Product Carbon Footprint (PCF) data.

Secure communication between middleware and external platforms is facilitated via standardized REST APIs employing the OpenAPI standard, with robust authentication mechanisms utilizing OAuth 2.0 and OpenID Connect protocols. Data integrity and authenticity are further ensured through digital certificates and signatures, with end-to-end encrypted data exchanges. The middleware incorporates Apache Kafka for event-driven architecture, providing efficient, real-time data streaming capabilities crucial for dynamically updating and synchronizing data across platforms. Additionally, a user-friendly graphical interface, ideally developed using Angular, simplifies configuration management, enabling intuitive management of database connections, user permissions, product master data, and audit logs. This comprehensive middleware solution significantly enhances data interoperability, security, and flexibility, laying a solid foundation for scalable and verifiable sustainability reporting within the steel industry.

CONCLUSIONS AND FUTURE WORK

This study presents a modular and scalable architecture for DPPs tailored to the specific needs of SMEs in the metal processing sector. Through the pilot implementation at Mannstaedt GmbH's hot rolling mill, the proposed system demonstrated the feasibility of real-time CO_2 tracking and seamless DPP generation using Python-based interfaces, RESTful APIs, and secure integration with SAP ERP systems. The data model aligns with Catena-X semantic standards and ECLASS classifications, while privacy and role-based access are ensured via an attribute-based access control system. These results validate the system's capability to meet the regulatory demands of the Ecodesign for Sustainable Products Regulation (ESPR) and support circular economy goals.

Steel is a critical material in automotive manufacturing, making the integration of green steel DPPs into Catena-X essential for enabling standardized, traceable, and low-carbon material flows across the industry's supply chain. For this reason, future work will focus on integrating with Catena-X and Tractus-X platforms and contributing to the evolution of DPP-related standards, ensuring interoperability and broader industry adoption. Furthermore, various initiatives and standardization efforts such as CEN-CENELEC Joint Technical Committee (JTC 24) and UNTP are continuously monitored, and the results will be integrated into the DPP architecture for green steel.

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Fully automated antimixup solution with LIBS technology, ensuring 100% check of the bar and billet proven over years of process operation

Amit Ahsan[1], Ardian Gojani[1], Martin Sprunk[1]
[1]SECOTPA analytics GmbH
Rheinstrasse 15B, Teltow, Germany, 14513; Phone: +49 3328 35403-0
Email: Amit.Ahsan@secopta.de

Steel mills face growing pressure for fault-free, mix-up-free shipments due to rising product variety and tighter lead times. Frequent grade changes increase the risk of material mix-ups, especially since traditional gap-based separation reduces productivity. Traditional identification methods often fail due to radiation use, long measurement times, or incompatibility with surface scale layer. As part of smart manufacturing (Industry 4.0), Laser-Induced Breakdown Spectroscopy (LIBS) offers a fast, non-contact, and fully automated solution for accurate material identification across production stages.[1,2]

KEYWORDS: LIBS, Mix-up detection (PMI), quality control in rolling mill, automated inline sensors

DISCUSSION

In inline spectroscopy-based Positive Material Identification (PMI) systems such as Laser-Induced Breakdown Spectroscopy (LIBS), the Matching Factor (MF) quantifies how closely a measured elemental spectrum aligns with a predefined reference. This reference typically originates from the melt shop's certified composition values. During the LIBS analysis, each process sample undergoes evaluation where predicted elemental concentrations are statistically compared to the reference values. The MF according to equation (1) is computed assuming a Gaussian distribution, incorporating three parameters: the reference concentration (*c_ref*), the LIBS-measured value (*c_measured*), and the individual measurement uncertainty (*error_element*), derived from customer-specific calibration data. This statistical framework ensures that elemental measurement variations are properly accounted for. The resulting MF is then compared to a preset threshold value. If the MF exceeds this threshold, the sample is deemed a valid match—confirming the material's identity. This method provides a robust, quantitative basis for high-confidence, inline material verification within modern production lines.[3]

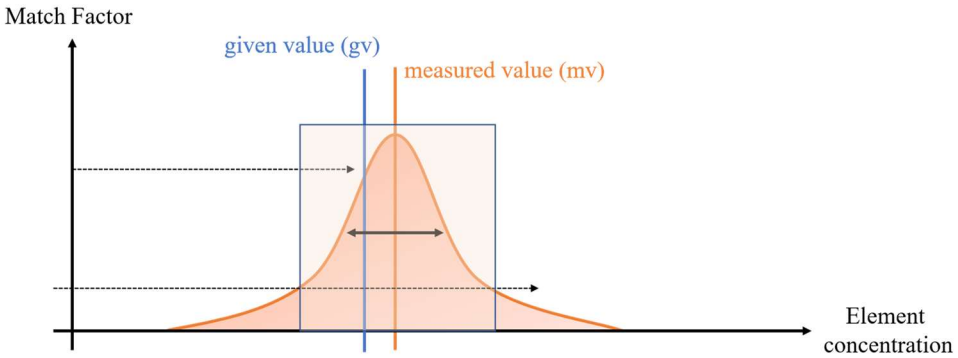

Figure 1. Illustration of matching factor necessary for PMI

$$MF = \frac{1}{\sqrt{2\pi}}\, e^{-\frac{1}{2}\left[\frac{[c_{ref} - c_{measured}]}{error_{element}}\right]^2} \quad (1)$$

LIBS IMPLEMENTATION IN PROCESS OPERATION

Depending on mix-up risk, LIBS PMI sensor can be integrated at various stages—such as the finishing line or before reheating furnace.[4] It is fully compatible with MES systems, allowing swift corrective action during material handling. Based on real life process experience, 100% antimixup check of material can be ensured with 99.6% accuracy.

Figure 2. FiberLIBS inline PMI device installed in the finishing line of bright bar

CONCLUSION

LIBS integration into quality control systems helps reduce errors, minimize scrap, and improve traceability. Unlike conventional methods, LIBS does not rely on indirect indicators but directly verifies material grade, making it especially valuable for high-precision manufacturing. As LIBS technology becomes more automated and robust, its role in modernizing and optimizing rolling mill operations is expected to grow significantly.

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Crafted Scrap: Scrap Yard Automation and Advanced Sensors

Alexander Reiter, Andreas Melcher, Andreas Rohrhofer – Primetals Technologies Austria GmbH

Steel circularity represents a sustainable strategy aimed at maximizing reuse of steel material, significantly contributing to the decarbonization of steel production. This approach encompasses the sustainable design of steel end products, resource-efficient steelmaking, and the recycling of steel products. Resource-efficient steelmaking is achieved through electric arc furnaces or converters prioritizing the use of recycled charging materials like steel scrap while minimizing the use of virgin materials such as pig iron or hot briquetted iron. Optimizing energy use and carbon footprint in these processes necessitates a thorough understanding of the composition of scrap portions charged into the melting unit to adjust process parameters accordingly. The recycling process involves collecting and pre-processing scrap through cutting, shredding, or cleaning. Efficient sorting, supported by chemical and/or optical analysis, is crucial for providing scrap of defined composition, which is essential for producing high quality steel grades with strict requirements. The target steel grade and the steelmaking process define the required quality and properties of scrap charges. Scrap compositions especially processed to meet these requirements are termed crafted scrap.

This paper presents a system of advanced sensor-based applications designed to determine the quantity and quality of scrap and track individual scrap portions throughout their lifecycle at a steel plant. It details how scrap quality is assessed using artificial intelligence-based camera image analysis for scrap type classification and detection of undesired objects, with the result applied to scrap pre-processing and sorting as well as inspection of incoming deliveries. The assessed quality is then used as the input for the scrap processing and composing system whose output is crafted scrap. Additionally, this contribution demonstrates how scrap quantity is estimated by creating volumetric maps of scrap yards and containers. A comprehensive scrap tracking approach is also outlined, covering delivery by train or truck, material handling, scrap processing, manipulation into scrap baskets or chutes, and finally charging into melting units, facilitating real-time inventory management. Practical implementations at an electric steelmaking plant confirm the effectiveness of these approaches.

KEYWORDS: SCRAP – GREEN – RECYCLING – CIRCULARITY – STEELMAKING – DIGITALIZATION – SENSORS – AI

INTRODUCTION

The steel industry is under increasing pressure to reduce carbon emissions and improve resource efficiency. Scrap-based steelmaking offers a viable path forward, but its success hinges on the ability to control the input material quality. Steel circularity has emerged as a cornerstone of sustainable metallurgy, aiming to reduce the environmental footprint of steel production by maximizing the reuse of steel materials. This paradigm shift supports the decarbonization of the steel industry through three primary pillars: sustainable product design, resource-efficient steelmaking, and comprehensive recycling strategies. Among these, resource-efficient steelmaking—particularly via electric arc furnaces (EAFs)—relies heavily on recycled materials such as steel scrap, minimizing the use of virgin inputs like pig iron or hot briquetted iron (HBI). Traditional scrap yards lack the infrastructure to assess and manage scrap composition dynamically, leading to inefficiencies and quality issues.

The variability in scrap composition presents significant challenges to process control, energy efficiency, and final product quality. To address these challenges, this paper introduces a sensor-driven system for scrap yard automation, enabling the production of crafted scrap—scrap tailored to meet specific steel grade requirements. The system integrates advanced sensing technologies, artificial intelligence (AI), and real-time tracking to optimize scrap handling and processing. Recent advances in sensor technology and AI offer new opportunities to automate scrap yard operations. By leveraging image analysis, LIDAR mapping, and chemical sensing, it is now possible to classify, quantify, and track scrap materials with high precision. This paper builds on these innovations to propose a comprehensive system for producing crafted scrap.

METHODOLOGY

Sensor-Based Scrap Classification

Incoming scrap deliveries are inspected using AI-enhanced camera systems. These systems are trained to classify scrap types [1,2] (e.g., shredded, heavy melt, turnings) and detect undesired objects (e.g., non-ferrous metals, plastics, hazardous materials). The image data is processed using convolutional neural networks (CNNs) trained on a diverse dataset of scrap images. Classification results are used to guide sorting and preprocessing decisions. Undesired materials are removed from further processing. Information gained in the classification process supports automated claim management towards scrap suppliers.

Volumetric Mapping

To estimate scrap quantities, LIDAR or radar sensors mounted on mobile platforms or fixed installations scan scrap piles and containers. The resulting point clouds are converted into volumetric maps using 3D reconstruction algorithms. These maps provide real-time inventory levels, volume-to-weight estimations based on material density and spatial distribution insights for optimized material handling.

Scrap Tracking System

A digital twin of the scrap yard is maintained using RFID tags, global and local tracking systems, and sensor data integration. The tracking system covers delivery logistics such as truck/train arrival and unloading, material flow on conveyor belts, cranes and in shredders, scrap basket composition and charging events. This enables real-time traceability of each scrap portion from arrival to melting, supporting inventory management, process control and optimization.

Crafted Scrap Composition Engine

Based on the classified and quantified scrap inventory, a composition engine selects and blends scrap portions to meet target steel grade specifications. The engine considers chemical and physical properties as well as process constraints amongst others. Scrap delivered from external suppliers or internal sources is processed and mixed in a manner to achieve the desired scrap composition specification.

IMPLEMENTATION

The proposed system was implemented and is currently in operation at an electric steelmaking plant in collaboration with industry partners. Improved scrap classification accuracy, enhanced inventory control, optimized scrap blending and reduced carbon footprint are the investigated key topics.

CONCLUSION

The integration of sensor technologies into scrap yard operations marks a significant advancement in steel circularity. By enabling precise control over scrap quality and quantity, the system supports both economic and environmental goals. Challenges remain in scaling the system to even larger facilities and integrating with legacy infrastructure.

Future work will focus on expanding the AI model to include more scrap categories and contamination types and integrating spectroscopic sensors for real-time chemical analysis.

Crafted scrap represents a transformative approach to scrap management in steelmaking. With advanced sensors, AI, and digital tracking, it is possible to produce scrap batches tailored to specific process and product requirements. This not only enhances steel quality but also supports the broader goals of sustainability and circular economy in the metallurgical sector.

The successful implementation at an electric steelmaking plant confirms the feasibility and benefits of this approach. As the industry moves toward greener practices, sensor-driven scrap yard automation will play a pivotal role in shaping the future of steel production.

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Metallurgical Quality Assessment With AI Vision Technology

Elena-Briana-Boeru – Sapotech Oy, Finland
Eemil Kiviahde – Sapotech Oy, Finland
Saku Kaukonen– Sapotech Oy, Finland

For years, metallurgical production has relied on imperfect inspection methods, often detecting defects too late, leading to wasted energy, time, and costs. Delayed detection also prevents intervention in defect formation mechanisms. Sapotech Oy aims to transform quality assurance with a real-time defect detection system, combining AI-driven prediction with a plug-and-play imaging solution. This innovation enhances automation in metal casting, reduces the carbon footprint of steel plants, and minimizes workplace injuries.

The proposed study examines several artificial intelligence blocks that can be plugged into our current UNet3+ architecture to reduce latency in the image-taking-to-defect-detection process, allowing for real-time identification of flaws. The approach takes images from our imaging devices and feeds them through an initial stage of the UNet3+ architecture, the suggested computer vision blocks, and then the rest of the architecture to output all the locations and types of the visualized defects. One of the primary benefits of this technique is the ability to run the blocks on different processing units, which greatly parallelizes the overall design and increases processing performance.

The effectiveness of our approach is evaluated in terms of processing speed versus required hardware, precision, and true positive versus false positive rate. Future enhancements of our solutions include introducing tundish-level sensor data for an early detection of defects and paving the way to fully automating the metallurgical casting process.

KEYWORDS: AI – COMPUTER VISION – QUALITY ASSURANCE – AUTOMATED DEFECT DETECTION - PARALLELIZATION

INTRODUCTION

Visual inspection has long been the standard for detecting casting defects - but it's limited, especially on hot surfaces where human access is unsafe and detail is hard to see. Despite the need for early-stage quality checks, inspection often happens too late, leading to reprocessing, safety risks, and high CO_2 emissions (1–3). In 2022, 91% of steel sites reported Potential Serious Injuries and Fatalities (PSIF). Globally, the steel industry produced 1.92 t CO_2 per ton of crude steel, totalling over 3.6 Bt in 2023 (4,5).

Over the years, quality assurance in steel plants has gradually started to change from manual visual inspection to machine-assisted approaches using computer vision methods and deep learning architectures. Convolutional Neural Networks and UNet-based solutions have proved useful in automated defect detection, oftentimes outperforming humans in consistency and accuracy. However, many of these models suffer from high latency, being bound by rigid hardware requirements, and limited integration with upstream data like tundish-level sensors. Almost all of them operate reactively, only detecting defects after they appear, therefore limiting the capabilities of early interventions and defect prevention. (6)

This study attempts to bridge these gaps by defining and testing two methods. The first is a Linear Recurrent Unit (LRU)(7) based method, which attempts to add a plug-and-play architectural unit meant to parallelize and enhance the processing of raw camera stream images. The second method is a Context Recurrent Neural

Network (Context RCNN) (8) based architecture, which leverages the detection power of Faster or Mask RCNN (9) architectures while also taking into consideration the temporal evolution of the data. Both of these methods are meant as an enhancement to our already successfully tested Unet3+ architecture. The main purpose is to achieve results that are as close as possible to real-time detection while also paving the way for temporally acquired tundish level sensor data integration in order to develop in future works early detection and prevention solutions.

QUALITY ASSURANCE IN CONTINOUS CASTING

Continuous casting is an important metallurgical technique that converts molten metal into semi-finished products like billets, blooms, or slabs, which are then treated into final shapes (10). This process has become a vital aspect of contemporary metal production, notably in the steel and non-ferrous industries, because of its high efficiency, cost-effectiveness, and ability to reliably create high-quality products.

QA (Quality Assurance) in steel casting begins with verifying the chemical composition of molten steel to ensure specification compliance. Equipment, including tundishes and ladles, must be inspected for wear or cracks to prevent contamination or dangerous failures, which can lead to irreparable damages to the continuous casting process or, even worse, the loss of human life.(11)

During the actual casting, the molten steel temperature must be closely observed to avoid solidification inconsistencies. The casting speed also needs to be precisely controlled to ensure uniform hardening and reduce the risks of surface or internal defects.(11)

Possibly one of the most important steps in the continuous casting process is the visual inspection of the solidified metal surface after the strand is cut into the desired lengths. The dimensions of the products are also checked to ensure adherence to tolerances. Multiple tests are made to identify porosity, cracks, or inclusions which affect the structural integrity of the metal. Finally, visual surface defects are identified and marked by personnel, which can be quite dangerous since the metal semi-products are still over 460 degrees Celsius.(11)

Reveal Cast – Automatic Surface Inspection System

The steel industry has relied on automatic surface inspection systems (ASIS) for decades (12). Typically, the systems are installed in hot and cold rolling mills, while surface inspection technologies for continuous casting are often unavailable. The Reveal Cast system represents a cutting-edge innovation for the monitoring and evaluation of the quality of intermediate and final metallurgical products, including those processed at elevated temperatures. By providing both real-time visual and numerical data, the system enhances manufacturing efficiency and ensures superior product quality (13).

The system comprises several key components that can be seen in Fig.1 (14): cameras, a high-speed illumination module, and a centralized control cabinet. Together, these elements enable the automated detection of defects while also allowing for manual annotation when necessary. Its advanced capabilities include precise high-speed laser/LED illuminated imaging, comprehensive surface inspection, infrared imaging, dimension and topographic measurements, among other functionalities. Typically, in continuous casting, the Reveal CAST is installed after the point in which the strand is cut.

A distinguishing feature of the Reveal Cast system is its seamless physical integration into existing manufacturing constructions. Installation is very efficient and streamlined according to process workflows. Often, Reveal CAST installation can be performed without any interruption to production processes. In some cases, the installation can even be performed by the customer with minimal supervision. Furthermore, the system is equipped with an intuitive browser-based user interface, ensuring ease of use for operators with varying levels of expertise in digital technologies.

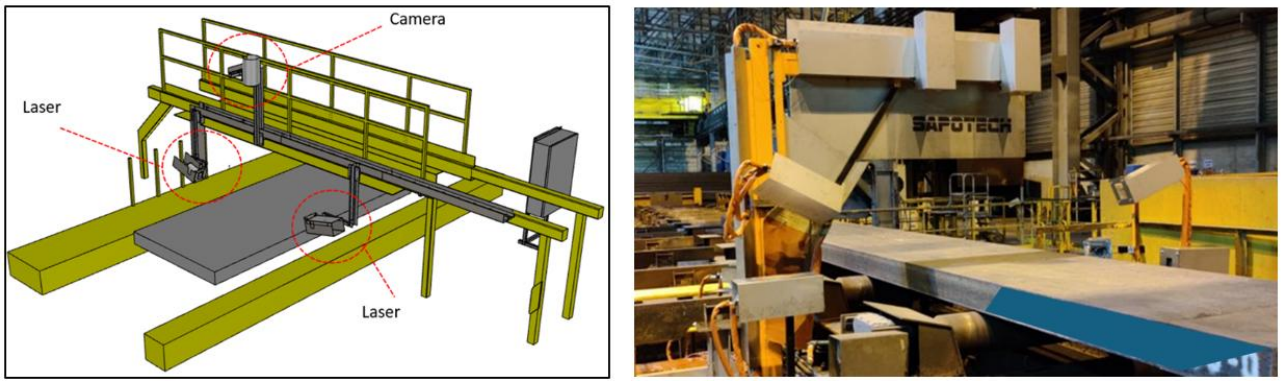

Fig.1 - Schematic of Reveal CAST (on the left) and system installed in a factory (on the right)

Artificial Intelligence in Quality Assurance

Artificial Intelligence (AI) and Deep Learning are altering how innovation occurs in a variety of disciplines. This shift is most obvious in fields that need continual visual surveillance and human intervention. In such situations, computer vision systems backed by machine learning have emerged as effective tools, producing outcomes that frequently outperform human capabilities. These technologies are already having a significant influence in a variety of fields, including imaging-based medical diagnosis, animal population tracking, and traffic management in smart cities.(15)

Despite these advances, a considerable issue remains. The success of these models frequently comes at a high computational cost. Deep learning architectures, while strong, are typically resource-intensive, necessitating high-performance hardware and significant energy input. This raises challenges to adoption, particularly in environments where computer infrastructure is limited or environmental sustainability is a concern. As a result, there is an increased demand for smarter, more efficient architectures - models that can improve early defect catching rates and prediction speeds. Balancing accuracy and efficiency is now at the forefront of deep learning research and striking this balance is critical to broadening the reach of AI-powered solutions across sectors.(15)

In our case, we want to ensure that our solutions work towards reducing steel plants CO_2 emissions to the minimum while maintaining maximal production rates. Therefore, employing solutions that are as performant as possible is a core requirement for all our work.(16)

METHODOLOGY AND COMPARATIVE STUDY

The hereby methodology was used to design, implement, and evaluate two real-time defect detection models closely mimicking the LRU (7) and Context RCNN (8) for steel surface inspection. The goal was to assess their accuracy, speed, and reliability in classifying and localizing surface defects under conditions similar to those in high-speed steel production lines.

To simulate real-world deployment, both models were tested on continuous image streams, mimicking video frames from high-resolution cameras on the production line. This differed from our current system, which introduces latency through pre-sampling. By replicating real-time input, we could assess not just detection accuracy but also responsiveness and throughput.

Both LRU and Context RCNN were evaluated for multi-class defect classification and spatial localization. An additional binary classification step was applied to Context RCNN due to its two-stage design. The models shared the same encoder and were integrated into a common architecture, with their outputs serving as inputs to a U-net(17) module.

Testing conditions were nearly identical, with the dataset adapted slightly to fit each model's input format while preserving its temporal integrity. Evaluation metrics included detection accuracy, IOU-based localization precision, and inference time per frame - critical for real-time viability.

Overall, this approach aimed to uncover practical trade-offs between detection performance and computational efficiency, offering valuable insights for deploying AI-based inspection systems in the steel industry.

Dataset Analysis

At its core, the pipeline began the data outputting process by fetching data samples from a production-scale database. These samples included both high resolution images and their corresponding defect annotations made by specialists in the field. Once retrieved, the images were transformed into tensors, containing spatial information such as heigh and width but also the number of color channels (3 – for the RGB format).

Subsequently, using the annotations, semantic label masks were generated for each image. These masks had the same spatial size as their corresponding image, but were produced in one-hot encoded format, capturing the detailed spatial information for each class at a pixel level. Following this, a weighting tensor was created based on the semantic labels, its use being to balance out the influence of clean regions and various defect classes during training. The complete workflow and structure of the datapipe can be observed in Fig.2:

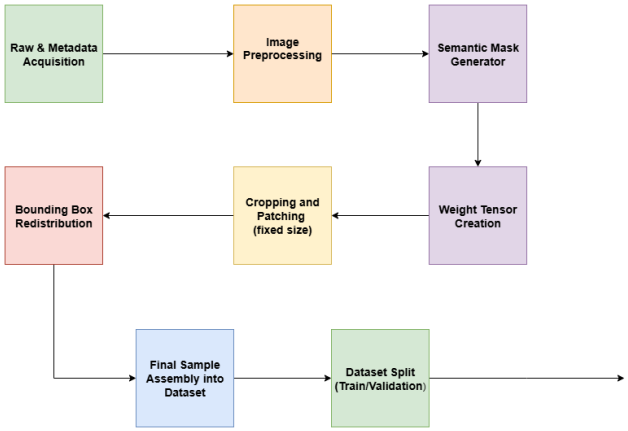

Fig.2 - Datapipe flow diagram.

Beyond spatial segmentation, the pipeline can generate data structures that express temporal continuity. This is accomplished via a vertically sliding segmentation approach, which divides images into successive, full-width pieces of identical height and width. These segments are processed in a manner that simulates temporally progressive sampling, keeping the sequence and spacing of frames as would be found in an industrial imaging system. Notably, matching annotations are addressed with the same logic to ensure that input characteristics and labels remain spatially and semantically aligned throughout the transformation process. This method uses dynamic padding to ensure that all output sequences correspond to expected dimensional formats, particularly when the source picture dimensions are not completely divisible or result in uneven segmentation. This stage standardizes the data's structure while avoiding semantic distortion, ensuring compatibility with batch processing and models that require fixed-size temporal windows.

Taking into consideration each bounding box's height and spatial location with respect to the cropping window and the original image coordinates, this method redistributes the whole bounding box tensor over the patches that are created. The algorithm adds the bounding box information to the associated cropped tensor patch after identifying which of the consecutive patches each bounding box overlaps with. This guarantees excellent precision between the original annotations and their representation inside each successive patch by preventing both repetition and omission of fault labels. To ensure that we have a static number of patches per batched sequence, we simply add a random number of clean boxes in addition to the defect ones in the patch if needed.

The clean boxes never overlap with the defect ones. This approach works because in an image we mostly have clean pixels rather than many defective instances, as can be seen in Fig.3.

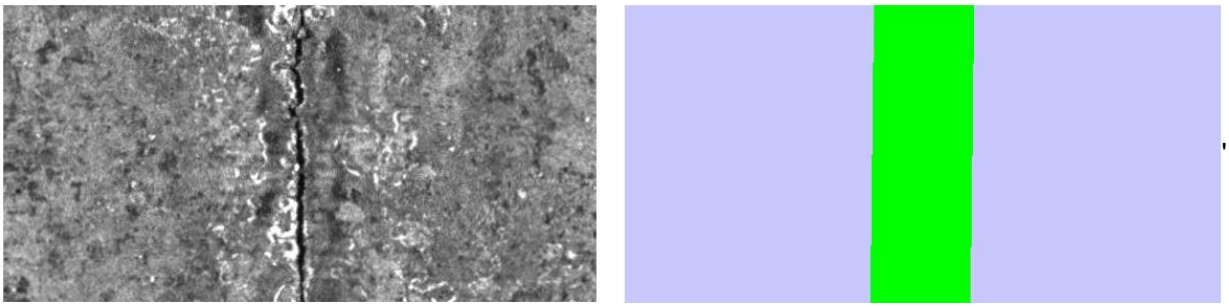

Fig.3 - Random slab image containing a crack (on the left) and associated label; In green – defect region (on the right)

Regardless of the employed strategies for building the structure of the dataset for the two chosen approaches, we had to work with highly imbalanced sample sets, the vast majority of them being so called “clean” samples, i.e. samples devoid of any defect, due to the distribution of defects in real-time data – the defects are rare, and when they are present they are not very sizeable, especially when comparing the height versus width ratio of the image versus the defect.

RESULTS AND DISCUSSION

LRU Architecture

The LRU Architecture, although seemingly more promising initially due to its light-weight architecture and unique plug-and-play structure (i.e. being a unit that can be added into any encoder - decoder structure) surprised us with its undermining performance. The model seems to get quickly overwhelmed by the “clean” class which causes it to output nonsense proposals. This can be easily discerned by a quick analysis of clean versus defect IOU metrics presented in Fig.4, in which we can see that the IOU metric for the clean class converges close to 1, while the mean IOU metric for the defects converges towards 0. The slight rise of the mean IOU defect metric tells us that initially the model does try to learn some helpful information but quickly gives up and default to generating only “clean” predictions, since that is most of the data it sees.

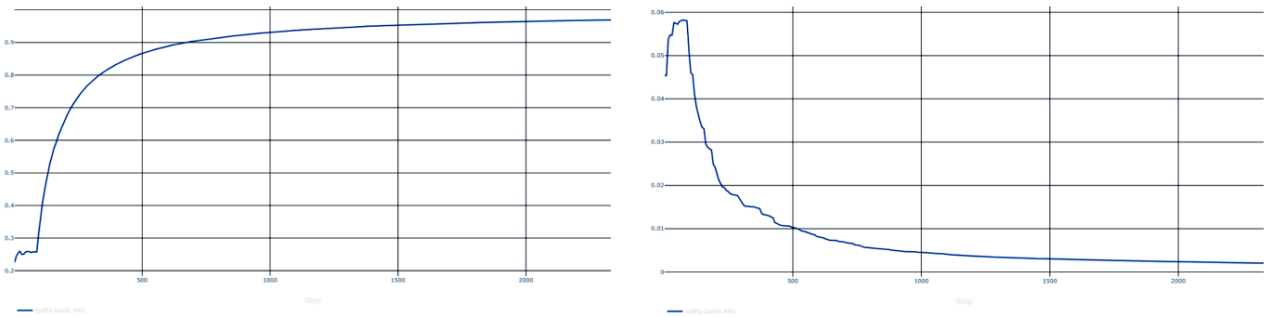

Fig.4 - LRU Clean sample IOU (on the left) and LRU mean defect IOU (on the right).

The rest of the metrics showcase the same poor performance as the IOU metrics, therefore we have determined that further visual testing is futile.

Context RCNN Architecture

The Context RCNN architecture on the other hand proved to be a more pleasant surprise compared to the LRU architecture. Although built on a Mask RCNN architecture (9), known for its complexity due to its two-stage learning approach, the results were strikingly better than the LRU architecture.

The reason behind this pleasant surprise is the core difference between the two architectures. While the LRU takes the whole image which has a massive amount of clean pixels versus defect pixels, the Context RCNN through it's Mask RCNN-like implementation uses an anchor system which effectively turns the whole task into a semantic segmentation problem, which is better suited to our use cases (i.e. defects with difficult shapes and size ratios whose feature information can easily disappear when mapping from one semantic level to another). One of the keys to our success is the development of a custom anchor generating architecture which better encompasses longitudinal thin defects (Fig.5) rather than traditional anchor variations (Fig.6), through outputting fixed height regions.

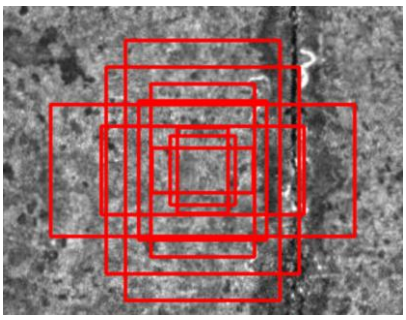

Fig.5 - Traditional anchor distribution.

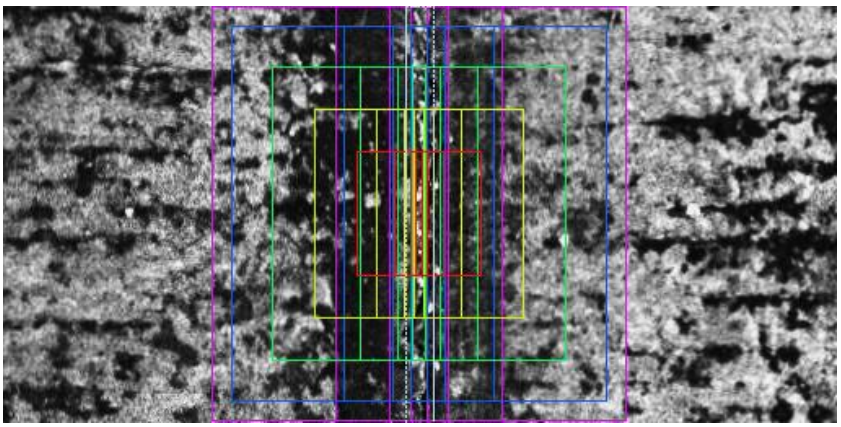

Fig.6 - Our custom anchor distribution; Different colors represent the different used scales; With dashed white line – defect bounding box.

Although our current approach has only successfully implemented and tested the first detection stage due to time and complexity constraints, further work being done to ensure the functionality of the whole two stage architecture to obtain refined results, the current unrefined findings uncover the massive potential of this architecture.

With only approximately 400 ms on average per training step and instant inference, the real-time usage capabilities of this architecture become evident. The good defect proposal generating results of this architecture further encourage us that this is a worthy pursuit, especially when compared to the defect detection capabilities of the other studied architecture. To be precise, as it can be seen from Fig. 7, the IOU

which measures the overlap of the proposals with the actual defect box encompassing the region of interest, we can observe that we start from a good place already due to the shape of the custom anchors, but with training we can even increase the overlap to over 65% while avoiding the exploding gradients problem.

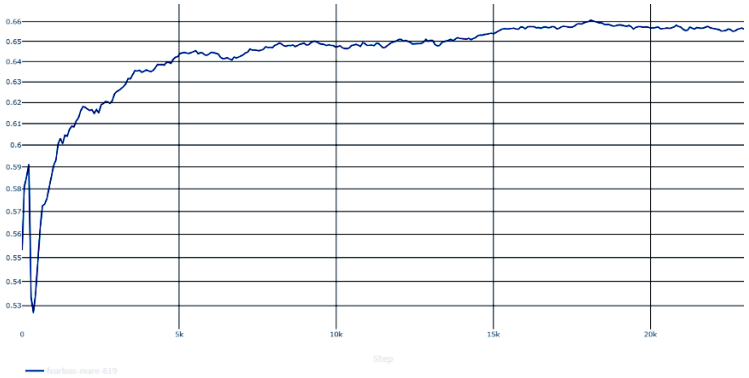

Fig.7 - Context RCNN Defect IOU.

The best and most telling test, however, is always the visualization of the predictions during the inference. As can be seen from Fig.8, where we have selected 10 random defect proposals out of the predicted ones for an arbitrary image, all the proposals (in green) regress to the same region which is overlapping with the defect region (in red). This means that our model is currently capable enough to correctly detect the general region in which a defect appears and have all its defect proposals identify the same region successfully, even if the regression is not yet perfect (i.e. the green region is not perfectly equal to the ground truth region bounded by the red box).

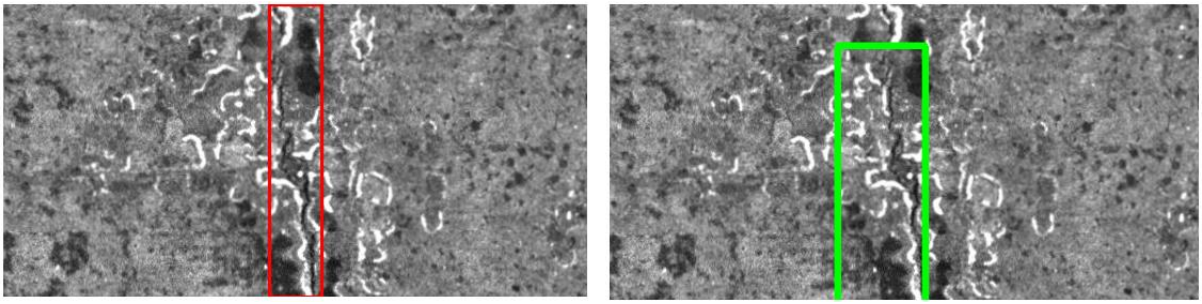

Fig.8 - Original image; In red – defect bounding box. Original image; In green – 10 random regressed defect proposals.

CONCLUSIONS

Although we are still in a crude stage of the Context RCNN architecture, its real-time potential benefits are evident, especially compared to the LRU architecture. As our research progresses, we expect to see even better final proposals with the addition of the second stages pixel-wise segmentation mask while maintaining our time-per-step under one second, thus being able to achieve real-time detection capabilities.

ACKNOWLEDGEMENT

We gratefully acknowledge the financial support from Business Finland within a project “Towards Fossil-free Steel 2” (No. 5867/31/2023).

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EXPLAINABLE AI FOR PROPERTY PREDICTION IN SCRAP-BASED STEEL PRODUCTION: A PUBLIC DATA IMPLEMENTATION

G. Millner[1], **T.-W. Wang**[1]

[1]**School of Materials Science and Engineering, Nanyang Technological University, 50 Nanyang Avenue, Singapore 639798**

Email: gerfried.millner@ntu.edu.sg

The global shift towards greener practices has introduced significant challenges for the material manufacturing sector. One key example is the need to increase the use of scrap metals in production to reduce the strain on natural resources and promote a circular economy. However, using scrap metals inevitably introduces impurities, which can greatly affect the properties of the final material. This potential drawback has led to the industry hesitation in adopting scrap metals in more general. To promote circularity in material manufacturing, it is crucial to improve the industry's understanding, confidence, and ability to work with scrap metals. One way to support this transition is by developing an AI tool that can assist in material production, enabling informed decisions to mitigate the impact of impurities. Such a tool relies on a deep understanding of the relationships between material properties, microstructure, processing methods, and composition. Building upon earlier work that successfully utilized industrial data to predict material properties through machine learning and explainable AI techniques, this research transitions to publicly accessible datasets. It presents a comprehensive data pipeline for predicting mechanical properties of steel from chemical composition and process parameters, and shows that known metallurgical relationships are effectively captured by the ML models, as confirmed through explainable AI. While the analysis focuses on public datasets, the methodology is readily transferable to industrial environments when appropriately adapted.

KEYWORDS: MACHINE LEARNING, STEEL COILS, MECHANICAL PROPERTIES, EXPLAINABLE AI, SHAP

INTRODUCTION

The global push for sustainable practices has intensified the focus on circular economy principles within the material manufacturing sector. Central to this transition is the increased utilization of scrap metals, which offers substantial environmental and economic benefits. Secondary steel-making via electric arc furnaces (EAFs) using scrap can reduce emissions by nearly 10 times compared to traditional blast furnace methods. [1] Despite these advantages, the incorporation of scrap metals into production processes presents significant challenges. Impurities such as copper and tin, commonly found in recycled steel scrap, can adversely affect the properties of the final material. While the effect on strength properties might even be beneficial, the opposite is often true for elongation and commonly the impact is not known exactly. [2] By modelling chemical composition effects, we can better understand and counteract the influence of both alloying and tramp elements on material performance. In earlier works the effects of alloying elements such as Nb, Mn, Cr, and Ti on the microstructure and mechanical behaviour of steels have been extensively studied [3, 4]. These elements play critical roles in refining grain size, controlling phase transformations, and enhancing strength through precipitation or solid solution strengthening mechanisms. Similarly, the interactions between Al and N, which lead to the formation of aluminium nitride (AlN) precipitates, have been the subject of considerable research due to their influence on grain coarsening behaviour and resultant mechanical properties [5, 6]. In contrast, the effects of residual or impurity elements, such as Cu, Ni, Sn, and Cr, which are commonly introduced through scrap recycling, remain less well understood. Duan et al. [7] simulated scrap-derived impurities by deliberately adding these elements to low-carbon steels and found that rising impurity content resulted in increased strength but a reduction in ductility. These studies rely on controlled experiments that isolate single variables by holding all other factors constant. While effective in determining individual effects, this approach overlooks potential interactions between parameters, limiting the generalizability of the findings to specific processing routes and compositions. However, significant work has also been done in the field of data-driven simulation techniques, where such limitations can be overcome. For example, Sieurin et al. [8] developed simple regression models with fitting parameters that must be adjusted for each newly investigated steel type. The prediction quality of such models can be further enhanced by using more advanced modelling techniques, as shown by Millner et al. [9]. They

Tab. 1. Overview of publicly available datasets for steel property prediction. The datasets used in this work—**Guo** [16], **Matbench** [17], and **MatNavi** [18]—are highlighted in bold with a gray background.

Name	observations	# features	chemical composition
Corroded Reinforcement Database [19]	1387	41	0
Guo [16]	63162	27	22
Matbench [17]	842	13	13
MatNavi [18]	915	16	14
Steel Fatigue Strength Prediction [20]	437	25	9
Steel Properties and Composition [21]	190	20	9
Steel Strength Data 2018 [22]	312	13	13
Steel Annealing Data [23]	798	35	1

used an industrial dataset with a model derived from Sieurin et al. [8] and Hutchinson et al. [10], and compared it with an artificial neural network that outperformed the model derived from literature. In addition, Millner et al. [11] showed in previous work that also other machine learning (ML) models have a similar prediction quality, despite being computationally simpler. Other recent notable work in this area include Lan et al. [12], Yang et al. [13] and Zippo et al. [14], who explored the relationship between chemical composition, specific process parameters, and critical mechanical properties such as tensile strength, yield stress, elongation, formability and ductility. While the datasets used in these studies are typically industrial in nature and restricted due to confidentiality, Guo et al. [15] have made their dataset publicly available [16] for their work on predicting multiple properties of steel.

This study summarizes publicly available datasets that are comparable to industrial datasets, where accessibility is often restricted. In addition, it presents a complete data pipeline—from data preprocessing to modelling—that can be applied to these and other similar datasets.

Section 1 describes the datasets used in this study and the process by which they were obtained. Section 2 outlines the implemented machine learning models and their respective configurations. Section 3 presents and discusses the results, including model performance and feature importance analysis to understand the role and impact of each variable.

1 DATA ACQUISITION AND PRE-PROCESSING

In this chapter, the datasets used in our study are presented. The focus of this paper is on publicly available datasets for the task of predicting the mechanical properties of steel coils based on chemical composition and process parameters in scrap-based steel production. To this end, we conducted a literature search to identify open-source datasets suitable for this purpose. Unfortunately, we quickly found that such datasets are rare. While we were able to identify relevant datasets, we acknowledge that this may not represent an exhaustive list. Nevertheless, only three dataset provided by Guo et al. [16], Matbench [17] and MatNavi [18] met our criteria of having at least 500 observations and offering a comprehensive chemical analysis. Other datasets were either smaller or lacked sufficient information on chemical composition. Our findings are summarized in Table 1.

1.1 DATASET DETAILS

The three selected datasets [16–18] all contain detailed chemical compositions, along with measurements for yield stress (YS), ultimate tensile strength (UTS), and elongation at fracture (EL). These values are summarized and compared in Table 2. Additionally, the Guo dataset [16] includes processing information, which is described in detail in the corresponding publication [15]. While the MatNavi dataset [18] provides three additional features, we chose to exclude two of them from our analysis and leave only the processing temperature in the dataset. This decision was based on either the lack of accompanying documentation, as it is the case for ”Alloy code”, or the observation that certain features, such as ”Ceq” (presumably carbon equivalent), are mostly zero, despite expectations to the contrary.

As target values, tensile strength, yield stress and elongation at fracture are used, as they are all stated in the mentioned datasets.

Tab. 2. Minimum and maximum values of chemical element concentrations across the three datasets in wt%.

Element	Guo		Matbench		MatNavi	
	min	max	min	max	min	max
Al	0.0043	0.3075	0.01	1.8	0.002	0.05
As	0.0016	0.0251	–	–	–	–
B	0.0	0.0049	–	–	–	–
C	–	–	0.0	0.43	0.09	0.34
Ca	0.0001	0.0135	–	–	–	–
Co	–	–	0.01	20.1	–	–
Cr	0.0001	1.1523	0.01	17.5	0.0	1.31
Cu	0.0047	0.4403	–	–	0.0	0.25
Mn	–	–	0.01	3.0	0.42	1.48
Mo	0.0001	0.5143	0.02	9.67	0.005	1.35
N	0.0	0.122	0.0	0.15	0.0025	0.015
Nb	0.0001	0.0645	0.0	2.5	–	–
Nb+Ta	–	–	–	–	0.0	0.0017
Ni	0.0023	0.4829	0.01	21.0	0.0	0.6
O	0.0	0.4	–	–	–	–
P	–	–	–	–	0.006	0.03
Pb	0.0001	0.0136	–	–	–	–
S	0.0001	0.036	–	–	0.003	0.022
Si	–	–	0.01	4.75	0.18	0.52
Sn	0.0001	0.0214	–	–	–	–
Ti	0.0	0.113	0.0	2.5	–	–
V	0.0	0.1999	0.0	4.32	0.0	0.3
W	0.0	0.0001	0.0	9.18	–	–
Zr	0.0	0.357	–	–	–	–

1.2 DATA PRE-PROCESSING

The data pre-processing in this work consists of data cleaning and normalization. Data cleaning is performed by excluding observations with missing information or unrealistic values, e.g. a yield stress of zero in the Guo dataset or a tensile strength of 6661 MPa in the MatNavi dataset. This leads to the following dataset sizes: 63122 observations and 27 features for the Guo dataset, 736 observations and 13 features for the Matbench dataset, and 913 observations and 14 features for the MatNavi datset. Normalization is done by z-score normalization after dataset splitting, to ensure the test dataset can not influence the norm and eventually the training of the training set.

2 METHODOLOGY

We employed a variety of machine learning (ML) models to predict the target values of our dataset, which has demonstrated strong performance in prior studies on similar data [11]. Specifically, we used Extreme Gradient Boosting (XGB) and Artificial Neural Networks (ANN). For comparison, we also included a linear model, ElasticNet (EN), which combines the strengths of L1 and L2 regularization and has shown good performance on both small and large datasets in studies such as Wang et al. [24] and Nayem et al. [25]. The hyperparameters of the models were optimized using the optuna framework [26], with the search ranges and implementation details provided in Table 3. Hyperparameter optimization was conducted separately for each model, dataset, and target variable, using 1000 trials in the case of EN and XGB. The architecture and optimization of the ANN is described in detail in Section 2.1.

2.1 ARTIFICIAL NEURAL NETWORK (ANN)

To model the non-linear relationships between chemical composition and tensile strength, we implement an Artificial Neural Network (ANN) using PyTorch. The network architecture consists of an input layer followed by multiple hidden layers. Each hidden layer includes a linear transformation, rectified linear unit (ReLU) activation, batch normalization, and dropout, followed by a final linear output layer that maps to the predicted target.

Tab. 3. Implementation and hyperparameters of the investigated ML models and search range. The used python version is 3.13.2

Model	Implementation	Hyperparameter	Default Value	Range
ANN	PyTorch 2.5.1	hidden_dims	-	list of 2–4 layers, each [32,2*len(input layer)] nodes
		learning rate (lr)	0.001	[0.0001, 0.1]
		weight decay	0.001	[0.000001, 0.1]
		batch size	32	[16, 128]
EN	scikit-learn 1.6.1	Alpha	1	[0.0001, 100]
		L1 ratio	0.5	[0.01, 0.99]
XGB	xgboost 2.1.1	alpha	0	[0.0001, 100]
		eta	0.3	[0.01, 0.3]
		lambda	1	[0.0001, 100]
		max_depth	6	[2, 20]

To determine the optimal network structure, we employ a genetic algorithm (GA) search, a method widely adopted for optimizing neural architectures in materials science applications, e.g., by Valentine et al. [27]. Each candidate architecture consists of 2 to 4 hidden layers, with each layer containing between 32 and twice the number of neurons in the input layer. A population of 20 networks over 20 generations is evolved. In each generation, networks are trained for 50 epochs using the Adam optimizer and evaluated based on their mean R^2 score in a 5-fold cross-validation. The top 50% of the population is retained for reproduction via single-point crossover, with a 10% mutation probability to introduce variability. This strategy enables dynamic adaptation of both network width and depth. Note that we had to restrict the maximum number of neurons per hidden layer to 512 for the Guo dataset due to computational limitations.

All candidate models are trained with a learning rate of 0.001 and weight decay of 0.001. We select the Huber loss function [28] for its robustness against outliers, which are common in mechanical property data due to process variation or measurement uncertainty, as demonstrated by e.g. Vilucchio et al. [29]. Early stopping with a patience of 20 epochs is applied, with training capped at 300 epochs. Dropout rates decrease progressively across layers, starting at 0.3 in the first hidden layer and reducing by 0.05 per subsequent layer (e.g., 0.3, 0.25, 0.2), allowing deeper layers to retain greater representational capacity.

After identifying the optimal network architecture for yield stress prediction, we conduct an optuna hyperparameter optimization with 500 trials for each target property.

2.2 EXPLAINABLE AI: SHAP

Beside calculating predictions, we explore how our models are making those predictions with explainable AI. SHAP (SHapley Additive exPlanations) [30] is used to identify the most influential features by quantifying the contribution of each feature through input perturbation and evaluation across all possible feature permutations, providing important insights into the impact of individual features within our models. We compute SHAP values for all our ML models to quantify the contribution of each feature to the predictions of the model. For the EN and XGB models, SHAP values can be calculated efficiently using the shap.Explainer from the shap Python package. In the case of our ANNs we used the shap.GradientExplainer and a background datasize of 1000 for the Guo dataset.

3 RESULTS AND DISCUSSION

In this chapter, the results of the regression tasks conducted in this study are presented and discussed. First, the outcome of the hyperparameter search is detailed in Subsection 3.1, followed by the regression results obtained using various ML models on the three datasets under investigation (Guo, Matbench, and MatNavi) in Subsection 3.2. Next, we analyse the models using feature importance tools in Subsection 3.3. Finally, in Section 3.4, we examine how the models generate their predictions and how the most influential features affect the results across different models.

3.1 Hyperparameter search

The results of the conduced hyperparmeter search, following the procedure specified in the previous chapter, are summarized in Table 4.

Tab. 4. Optimized hyperparameters for different models across datasets and target properties.

Model	Hyperparameter	Guo et al.			Matbench			MatNavi		
		YS	UTS	EL	YS	UTS	EL	YS	UTS	EL
ANN	hidden_dims	[171, 504]	[171, 504]	[171, 504]	[906, 124, 248]	[906, 124, 248]	[906, 124, 248]	[454, 142]	[454, 142]	[454, 142]
	learning rate (lr)	1.14E-04	1.40E-04	3.35E-04	1.08E-03	2.65E-03	7.39E-03	2.87E-03	7.12E-03	3.91E-03
	weight decay	1.29E-03	5.57E-04	9.69E-05	3.16E-06	1.29E-05	1.45E-06	1.28E-06	3.31E-06	1.53E-04
	batch size	128	128	128	32	128	32	128	128	64
EN	Alpha	1.02E-04	3.33E-04	3.08E-04	1.87E-02	1.89E-02	2.77E-02	7.87E-03	1.11E-02	9.91E-03
	L1 ratio	0.990	0.989	0.989	0.989	0.990	0.989	0.212	0.533	0.989
XGB	alpha	1.86	1.39	1.16	0.662	2.64E-03	4.21E-04	8.04E-03	1.63E-02	1.64E-03
	eta	4.99E-02	5.37E-02	1.76E-02	0.141	0.279	0.280	0.127	0.282	0.107
	lambda	14.43	0.384	5.41	57.47	9.97	71.75	1.21	11.71	0.004
	max_depth	10	10	10	8	4	7	4	4	5

The optimized ANN configurations vary in architecture and hyperparameters across datasets, suggesting sensitivity to data characteristics. Small regularization values, mostly below 1e-3, indicate that the ANN doesn't heavily overfit or that other regularization mechanisms (like dropout or early stopping) are in place.

A notable observation from the EN results is that regularization is significantly weaker for the Guo dataset, with the optimization process favouring almost exclusively L1 regularization in most cases. An exception is seen with the MatNavi dataset, where a combination of L1 and L2 regularization also emerges, indicating that variable selection does play a vital role.

The XGB results show noticeable variability in all major hyperparameters, with strong L1 regularization and deeper trees for the Guo dataset, pointing to the presence of noisy or redundant features that benefit from aggressive pruning and feature selection. In contrast, results with the MatNavi dataset exhibit smaller regularization parameters and shallow trees, pointing to a cleaner signal and less overfitting risk.

3.2 REGRESSION RESULTS

The resulting metrics of the 5-fold cross-validation runs with all used ML models and all datasets under investigation are plotted as barplots in Fig. 1 and given in Table 5 to 7.

Tab. 5. Mean $\pm$ standard deviation of yield stress (YS) predictions from a 5-fold cross-validation across the used models.

Dataset	EN (R^2 / MAE [MPa])	XGB (R^2 / MAE [MPa])	ANN (R^2 / MAE [MPa])
Guo	0.886 ± 0.003 / 30.363 ± 0.395	0.942 ± 0.002 / 20.315 ± 0.252	0.939 ± 0.002 / 20.961 ± 0.137
Matbench	0.473 ± 0.049 / 155.188 ± 4.450	0.558 ± 0.152 / 132.414 ± 23.040	0.769 ± 0.056 / 95.068 ± 7.323
Matnavi	0.820 ± 0.042 / 41.584 ± 4.773	0.915 ± 0.033 / 26.088 ± 5.448	0.964 ± 0.021 / 14.795 ± 1.409

Tab. 6. Mean $\pm$ standard deviation of ultimate tensile strength (UTS) predictions from a 5-fold cross-validation across the used models.

Dataset	EN (R^2 / MAE [MPa])	XGB (R^2 / MAE [MPa])	ANN (R^2 / MAE [MPa])
Guo	0.940 ± 0.002 / 21.311 ± 0.271	0.966 ± 0.002 / 14.965 ± 0.289	0.962 ± 0.003 / 15.727 ± 0.280
Matbench	0.605 ± 0.014 / 155.909 ± 3.510	0.701 ± 0.100 / 125.411 ± 16.728	0.828 ± 0.041 / 92.758 ± 9.023
Matnavi	0.669 ± 0.015 / 60.564 ± 3.726	0.917 ± 0.049 / 27.255 ± 11.000	0.965 ± 0.016 / 15.975 ± 2.872

Overall, the best results are achieved by models predicting tensile strength, followed closely by those predicting yield stress. Models predicting elongation at fracture perform the worst in this comparison, especially when using the matbench dataset. The results of ML models on the Guo dataset show similar prediction quality across all models, with very little variation in 5-fold cross-validation—likely due to the dataset's large size and low variance, which reduces sensitivity to the train/test split. The mean absolute errors are as low as 14.97 MPa for the prediction of UTS, indicating the potential application of these models for quality control and process monitoring. Results from the Matbench dataset show a

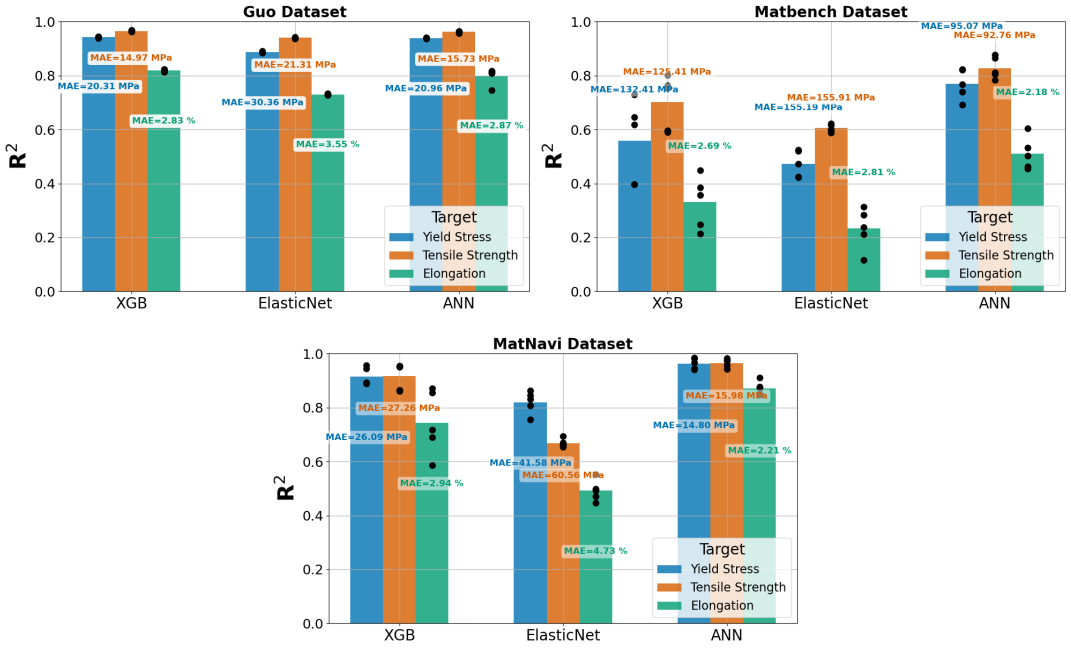

Fig. 1. Barplots comparing ML models (Artificial Neural Network (ANN), ElasticNet (EN) and Extreme gradient boost (XGB)) across three different datasets (Guo, Matbench and MatNavi). The height of the bar shows the mean value of the respective metric and model of a 5-fold cross-validation calculated with extrapolation data and the points show the individual results. The average mean absolute error of each cross-validation run is indicated as annotation.

Tab. 7. Mean ± standard deviation of elongation of fracture (EL) predictions from a 5-fold cross-validation across the used models.

Dataset	EN (R^2 / MAE [%])	XGB (R^2 / MAE [%])	ANN (R^2 / MAE [%])
Guo	0.731 ± 0.002 / 3.552 ± 0.036	0.819 ± 0.004 / 2.827 ± 0.007	0.800 ± 0.031 / 2.867 ± 0.025
Matbench	0.233 ± 0.076 / 2.815 ± 0.222	0.331 ± 0.098 / 2.691 ± 0.299	0.511 ± 0.061 / 2.177 ± 0.144
Matnavi	0.492 ± 0.039 / 4.735 ± 0.374	0.744 ± 0.119 / 2.936 ± 0.619	0.872 ± 0.026 / 2.210 ± 0.273

much larger performance gap between models, with ANN emerging as the clear winner. Cross-validation variability is also significantly higher, suggesting that the ML models may lack sufficient information in certain splits. In the MatNavi results, XGB performs notably better again, closing the performance gap with ANN. This highlights the importance of dataset-specific model selection, as supported by previous studies showing that model performance is highly dependent on dataset characteristics such as size, complexity, and feature distribution [31,32].

To further illustrate the capabilities of the ML models to accurately predict mechanical properties, Fig. 2 presents prediction plots for models trained on the Guo dataset. Only test data, obtained via a random train/test split, is shown. Additional plots evaluating model performance on other datasets are provided in the supplementary information. All of them show that most predictions are very close to the 45-degree line, indicating a near-perfect fit. However, predictions in low-density regions (such as high strength or elongation) exhibit significantly worse performance.

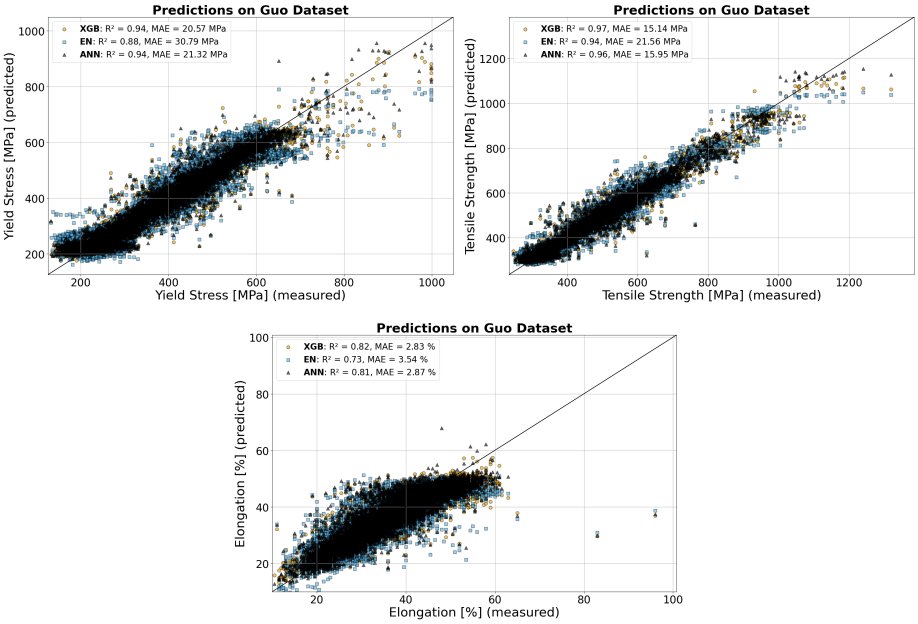

Fig. 2. Prediction plots showing predicted over measured values of models predicting YS, UTS and EL with models trained with the Guo dataset. The respective performance metrics are given in the legend.

3.3 FEATURE IMPORTANCE

In this Subsection, the results of our feature importance analysis conducted with SHAP is presented. In the Guo dataset, the carbon equivalent (Ceq) is the most influential feature, consistently ranking first across both models and all target properties, followed by Nb and Ti. In the Matbench dataset, elements such as C, Co, Ti, and Al are consistently among the top predictors of the strength parameters YS and UTS. However, models predicting EL from the same dataset perform poorly, and their predictions are considered unreliable. For models based on the MatNavi data, temperature emerges as the most critical feature. Additionally, V, Mo, and Mn are frequently identified as influential across all targets and model variants. In Fig. 3 some beeswarm plots are shown as examples, detailed beeswarm plots of all models and datasets can be found in the supplementary information, along with the calculated SHAP values. Previous research conducted by Millner et al. [9] suggested that C, N and P are among the most influential features in data driven models predicting tensile strength. As C, N and P are occupying interstitial sites in the ferrite lattice, due to their size, they enhance the strength of the material significantly. [8, 33] This is only partly reflected by our observations, as C does play an important role in the Guo dataset in form of the carbon equivalent (Ceq, see Eq. (1) [15]) and the Matbench dataset, but shows mediocre importance in the results from the MatNavi dataset. N does not play a very important role in all our models, according to the SHAP-values. While P is missing in Guo and Matbench data, it is also not among the top features in models using the MatNavi dataset.

The addition of substitutional elements can lead to the formation of multi-component carbides, which reduce the concentrations of both carbon and the alloying element in the matrix. This process can improve mechanical properties and contribute to microstructural stability. Typical strong carbide-forming elements in steel include Cr, Mo, Ti, V and Nb. [34] The strong effect of Nb and Ti in our models using the Guo dataset and Ti in models using the Matbench dataset suggest that such an effect is playing an important role in those datasets.

$$Ceq = C + \frac{Mn}{6} + \frac{Cr + Mo + V}{5} + \frac{Ni + Cu}{15} \tag{1}$$

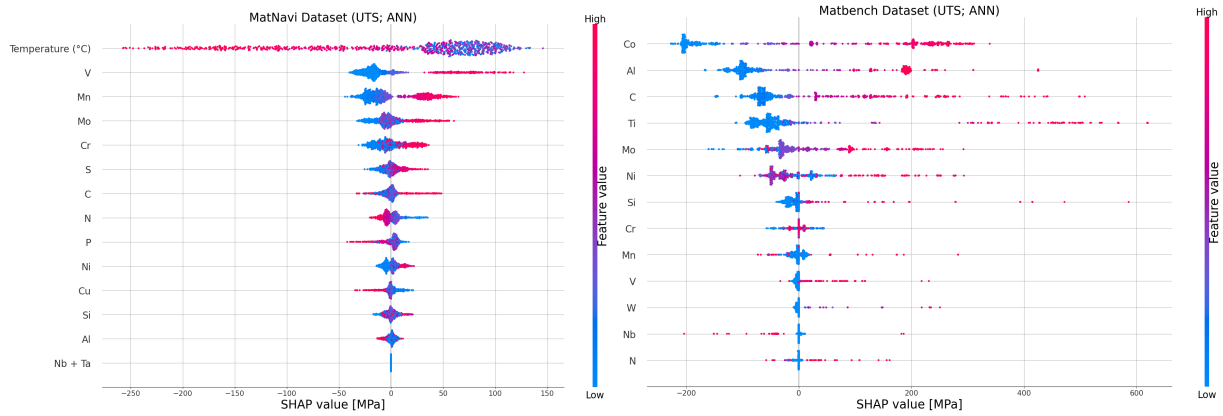

Fig. 3. Beeswarm plots of ANN models predicting UTS with Matbench and MatNavi dataset. The points are coloured according to their feature value.

3.4 IMPACT OF FEATURES

In addition to assessing overall feature importance, SHAP analysis provides local explainability by quantifying the impact of each feature in individual predictions. When SHAP values are plotted against feature values, only the most influential features tend to align well with established findings in the literature in our case. For instance, the carbon equivalent (Ceq) exhibits strong agreement between SHAP values from all models (ANN, EN and XGB) when applied to the Guo dataset. This observation aligns with the known solid solution strengthening effect [3, 4, 34]: Ceq, predominantly determined by C [15], is positively correlated with YS and UTS, and negatively correlated with elongation (EL), as illustrated in Fig. 4. Another illustrative case is that of Al in models trained on the Matbench dataset. The ANN, EN, and XGB models consistently indicate a clear strengthening effect of Al, accompanied by a reduction in ductility or elongation, as shown in Fig. 4, and expected from literature. [7, 35] Additional examples, along with the complete dataset required to reproduce the plots, are provided in the supplementary information.

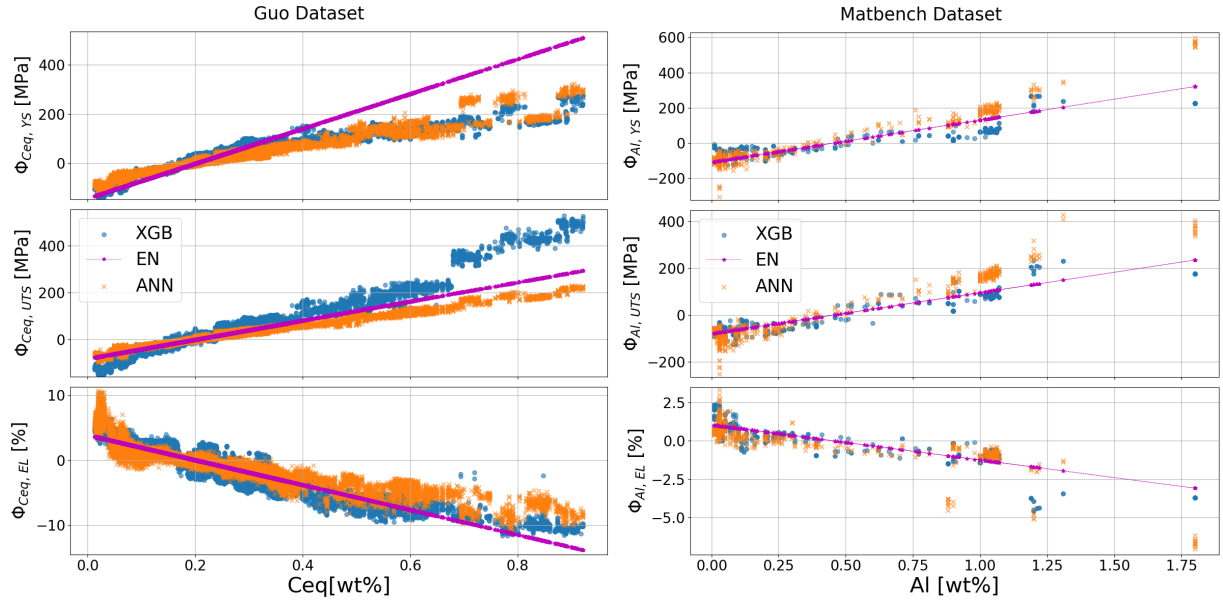

Fig. 4. SHAP dependence plots of models using Guo and Matbench dataset. $\Phi_{feature,target}$ . . . SHAP-value describing how much a specific feature in models predicting a target is changing the prediction.

4 CONCLUSION

In this work we presented a pipeline to predict mechanical properties of steel (YS, UTS and EL) from chemical composition and process parameters. Subsequently, we analysed the models using the explainable AI framework SHAP to identify important features and determine their impact within models that are often perceived as black boxes. We applied this pipeline to three publicly available datasets (Guo [16], Matbench [17], and MatNavi [18]) and demonstrated that ML models can accurately predict key properties of final steel products. We found that models predicting UTS and YS were more accurate than those predicting EL. Additionally, we showcased the ability of SHAP to identify the importance and influence of features in all of our models, while the impact of top-rated features compares well with findings in the literature.

In future work, more datasets should be made available to the public, advancing innovation in this field by enabling the application of these and similar techniques to more diverse data sources and accelerating progress. Besides that, microstructural information might help to improve the predictability of ML models further.

CONFLICT OF INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

DATA AVAILABILITY STATEMENT

All datasets used in this work are publicly available, see [16–18]. The code that was used to generate the results can be shared upon reasonable request. SHAP objects generated are shared in the supplementary information.

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SUPPLEMENTARY INFORMATION

The supplementary information of this paper are containing the calculated SHAP objects needed for reproducing all plots in Section 3.3 and 3.4, creating more SHAP plots and investigate the results on your own. Additional plots evaluating model performance on all three datasets (Guo, Matbench and Matnavi) are provided as well. They can be found on DR-NTU (Data): https://doi.org/10.21979/N9/NYRGAA

THE PIVOT ROLE OF MODELLING IN PROBLEM-SOLVING ISSUES IN CONTINUOUS CASTING OF STEEL: A PROJECT CLUSTERING EXPERIENCE IN THE EUROPEAN PROGRAMMES FRAME

Michele De Santis. Orlando Di Pietro- RINA Consulting- Centro Sviluppo Materiali SpA, Rome, Italy
Nora Egido Perez, Diana Mier Vasallo – SIDENOR I+D, Basauri, Spain
Christine Gruber - K1-MET, Linz, Austria
Kersten Marx, Marc Koester – Betriebsforschungsinstitut – Düsseldorf, Germany
Pavel Ramirez Lopez – SWERIM, Luleå, Sweden

Problem-solving in industrial processes relies on the adequate development and use of tools able to get insight and improved knowledge and know how on the phenomena behind the occurrence e.g, of factors affecting production quality and productivity. In steel production, this gains particular importance due to the need of following the increasingly severe market request and the unavoidable sustainability needs for producers – economic and environmental. To this scope, process control tools, supported by adequate sensoring in a digitalised and AI-based framework, are of outmost importance and increasing use.
A backbone for the process control architecture, when aimed at setting up tools for process management as digital twin working off- and online, is a reliable description of the phenomena behind the process, based on a validated modelling. In this view, continuous casting of steel shows a multi-fold approach based on single issues, as steel flow, solidification, heat transfer, behavior of oxides dispersed in steel, or integrating them into a complex and Multiphysics architecture. A significant number of these activity were funded by European programmes grants, allowing as outcome an improved knowledge enabling a more efficient development of tools supported by sensoring on-field able to process management, quality control and support decision. An example is given in this contribution, where it is shown the pivot role of modelling in continuous casting, allowing to fundamental knowledge and problem-solving (headlines of METACAST project), the approach joint to process monitoring to a definition of a digital twin for quality control minimizing defects (SUNSHINE) and another (SHELL-CRACK) where the modelling approach is used jointly with lab activities and hardware products to better drive their use and to ensure problem solving as well as regards to as-cast surface quality enhancement. All of these are funded by the European Research Fund For Coal and Steel Programme (RFCS).

KEYWORDS: STEEL, CONTINUOUS CASTING, MODELLING, PROBLEM SOLVING, DIGITAL TWINS, PROCESS CONTROL

PROBLEM AND APPROACH

As a starting point, there is the huge modelling potential achieved through RFCS projects to solve casting challenges in the European steel industry.
The recent advances in modelling refer to three main areas:

- fundamental research,
- industrial applications,
- decision-making.

On the other hand, the modern trend highlights the need of calling for a) improved models and time calculations, b) Multiphasic approach, c) Implementation for process control – AI tools.

This tendency can be summarized in Fig. 1[1]

[1] VALCRA Project, RFCS-GA No. 84719

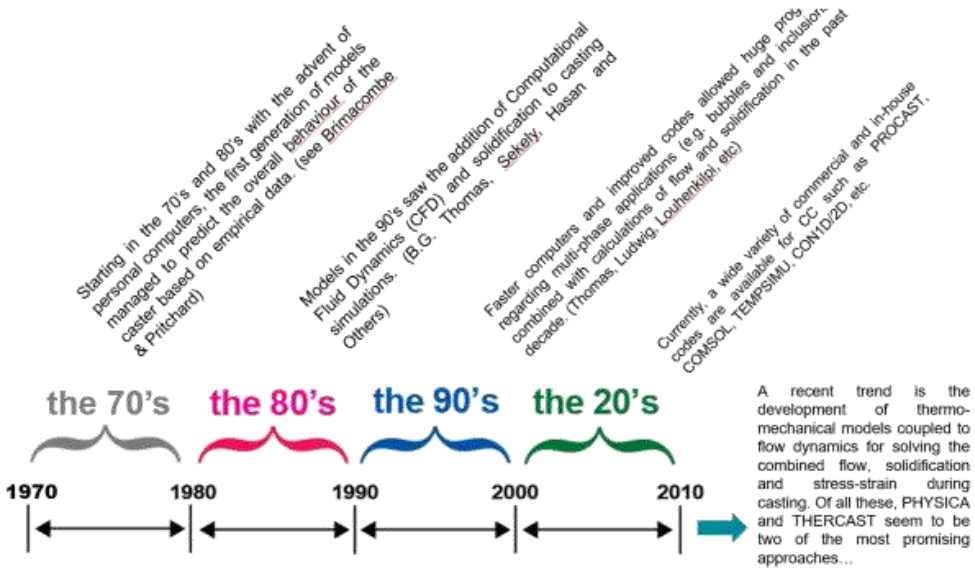

***Fig. 1** - Modelling trend/approach in the last 50 years[1].*

This is in line with the improved skill (also boosted by open training/dissemination events and targeting appropriate decision makers including researchers and managers), see **Fig. 2**.

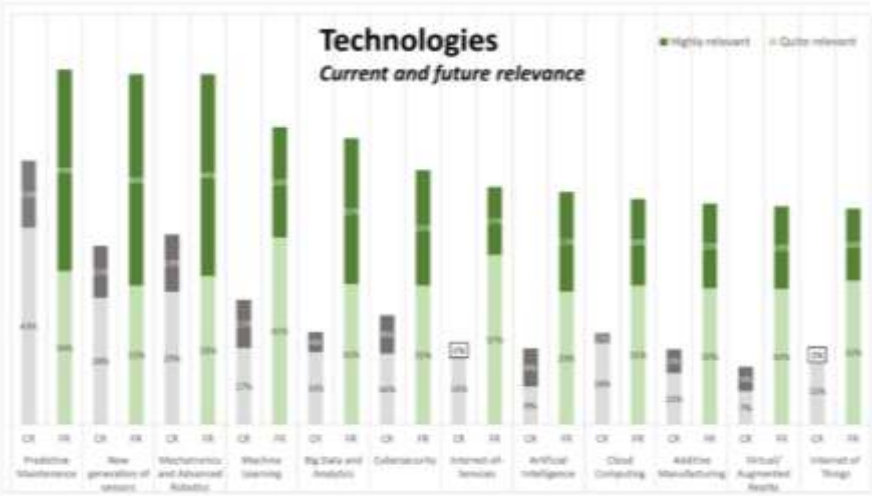

Figure 3: Current and future relevance of different technologies, proportion of job-profile-related assessments in which the technology was considered to be "highly" or "quite" relevant in the present and in the future (respectively).

***Fig. 2 –** Technology current and future relevance. From Blueprint "New Skills Agenda Steel": Industry-driven sustainable European Steel Skills Agenda and Strategy (ESSA)*

In this view, the EU Funding program support is evidenced by the storyline of the Research Fund of Coal and Steel priorities in the last 25 years[1] (see **Fig. 3**).

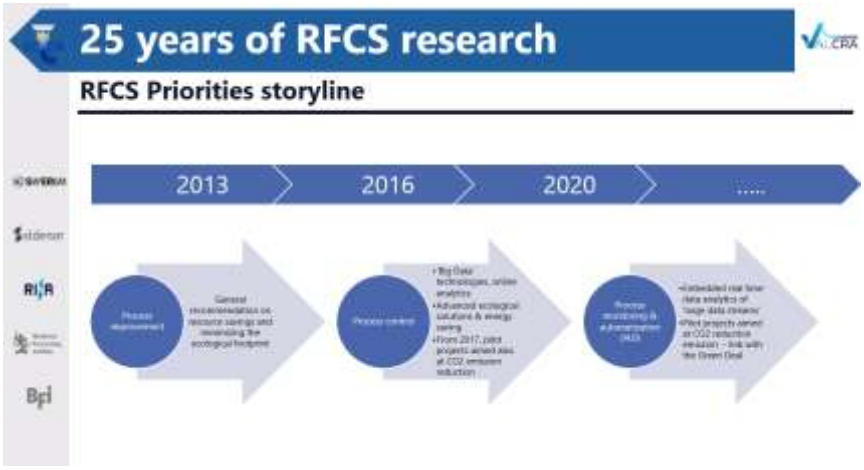

Fig.3 *– Trend of the Research Fund of Coal and Steel up to 2020[1].*

Project clustering (= grouping of related projects) offers significant benefits by fostering collaboration, knowledge sharing, and resource optimization. It allows for a more efficient and effective approach to project management, particularly within large organizations or when dealing with complex, interconnected initiatives.

To benefit from the clustering approach to technical issues, encouraged by the EU Commission to maximise the project outcomes and benefits for the stakeholders, three groundbreaking EU-funded projects on the world of continuous casting of steel were considered with a pivot role of modelling:

- METACAST (GA 101155952): A dissemination project coordinated by RINA-CSM; it builds a common ground for modelling in continuous casting. It leverages insights from past RFCS projects to unlock modelling potential for solving steel industry challenges

- SUNSHINE (GA 101157885): Coordinated by RINA-CSM, it develops AI-driven models and uses in-line sensors to detect defects early in the casting process. It aims to improve process control and product quality in real time.

- SHELL-CRACK (GA 101156718): Led by SWERIM, the project creates robust crack prediction criteria across the casting process. Using plant trials and smart sensors, it integrates material properties and process data to reduce casting defects. They deal with modelling science applied to quality, productivity, safety and innovation.

The dissemination activity is performed in close cooperation, leaning on social media (LinkedIn, e.g., https://www.linkedin.com/company/105728781/admin/dashboard/) where the projects are boosting each other, favoring exchanges among RTO, stakeholders and academia, creating and a 'modelling network' also with the support of an overarching account (ECCN, European Continuous Casting Network, set up in the frame of a former RFCS project[1]).

The final aim is to provide insights into the importance of modelling as tool functional to industrial problem solving, as well as Artificial Intelligence/Machine Learning feeding for process digitalisation as well as improved workers' skill vs the current challenges.

ACKNOWLEDGEMENTS
This study was carried out with a financial grant from the Research Fund for Coal and Steel of the European Community. The authors would like to thank the EU for supporting the ongoing METACAST project (contract number 101155952) for disseminating the main outcomes in the field of casting modelling.

Application of Deep Learning technique to improve the scrap quality

A. Petrucciani, V. Colla, M. Vannucci, A. Siddique - Sant'Anna School of Advanced Studies, TeCIP, ICT-COISP, Italy
M. Ometto, M.Meneghin, C. Pietrosanti – Danieli Automation S.p.A., Italy

In recent years, the exploitation of Deep Learning and computer vision to classify waste material has rapidly increased to automate recycling processes, increasing efficiency and reducing carbon footprint. Electric steelworks, which produce steel by recycling ferrous scrap, fit perfectly into this context. In effect, the identification and classification of different types of scrap is strategic to improve efficiency in steel production, promote implementation of Circular Economy principles and reduce CO2 emissions. In particular, to enhance the recycling of low-quality scrap material, it is fundamental to reduce the presence of impurities such as tramp elements (e.g. copper). Currently, scrap characterization and monitoring are still manually carried out, based on subjective assessment based on operators' experience. Therefore, the application of Deep Learning techniques for steel scrap classification is crucial to improve scrap recycling and exemplary shows that AI can be profitably applied in the metallurgical field to automatically assess the grade of each scrap piece.
In the present work, a Deep Learning model for the automatic detection and identification of the presence of copper in scrap is described. The created dataset consists of scrap images collected with the camera during the Horizon Europe Clean Steel Partnership project entitled "Purity improvement of scrap metal" (Ref. PURESCRAP - G.A. 101092168). The images, obtained in the test campaigns conducted at Stena Recycling facility, were labelled and exploited to train, validate and test the model. In particular, two models were developed based on the FasterRCNN + ResetX-101 architecture and YOLO architecture, and their performances were compared.

KEYWORDS: DEEP LEARNING - CIRCULAR ECONOMY – RECYCLING - SCRAP MANAGEMENT - STEELWORKS

1. INTRODUCTION

Efficient scrap management is crucial for ensuring both the quality and sustainability of steel production.
By accurately sorting scrap, particularly selecting materials with known composition and low contamination of tramp elements, the steel producers can guarantee the quality of steel, reducing the carbon footprint and improving the circular economy.
The tramp elements are difficult or sometimes impossible to remove during melting and refining processes, and, in the case of copper, even at concentrations as low as 0.1 wt %, lead to a loss of ductility and surface defects [1]. Without an effective classification and control at intake, recycled steel streams risk being increasingly contaminated over time, threatening their suitability for high-performance applications and undermining circular-economy ambitions [2]. Currently, impurity detection largely depends on manual inspections based on operator experience, which can be inconsistent, subjective, and labour-intensive.
To address this limitation, in the present work, two advanced image processing methods based on Deep Learning (DL) to detect copper in steel scrap are presented. Different datasets were created with images collected during the test campaigns at Stena industrial recycling facility in Sweden. Each image was manually labelled to identify the presence of copper-containing objects, thereby establishing a ground truth foundation for supervised learning and model evaluation.
Two state-of-the-art object detection architectures were implemented and assessed. The first is based on the Faster R-CNN with ResNeXt-101 backbone, known for its high detection accuracy and robustness in complex visual environments. The second model is built on the recently proposed YOLO architecture, which prioritises real-time detection capabilities with improved computational efficiency. Both models were trained, validated,

and tested on the annotated dataset to compare their performance in terms of detection accuracy, speed, and generalisability.

2. RESULTS

In general, the best performances in terms of mAP50 (Mean Average Precision) and FPS (Frame Per Second) are achieved by YOLO model for all the dataset.The inference speed of each model was measured in frames per second (FPS), a key performance metric for real-time applications.
In Table 1 the test results achieved for the last and largest dataset (Ground truth equal to 1174) are reported.

Tab. 1 - Results on Dataset 4.

Results					
Model	**mAP$_{50}$%**	**TP**	**FP**	**FN**	**FPS**
FasterRCNN	91.26	1096	131	78	2.46
YOLO	92.44	1098	99	76	11.74

The results demonstrate that all YOLO-based models significantly outperform the Faster R-CNN model in terms of inference speed. This is consistent with the lightweight, real-time design of the YOLO family of models, which are optimised for speed-efficient object detection.
From an industrial deployment perspective, a critical requirement is that the inference speed of the selected model should meet or exceed a minimum threshold of 10 FPS to ensure responsiveness and operational feasibility. In this context, the YOLO model satisfy this requirement.
Figure 1 presents selected true positive examples from the evaluation of the YOLO model on Dataset 4.

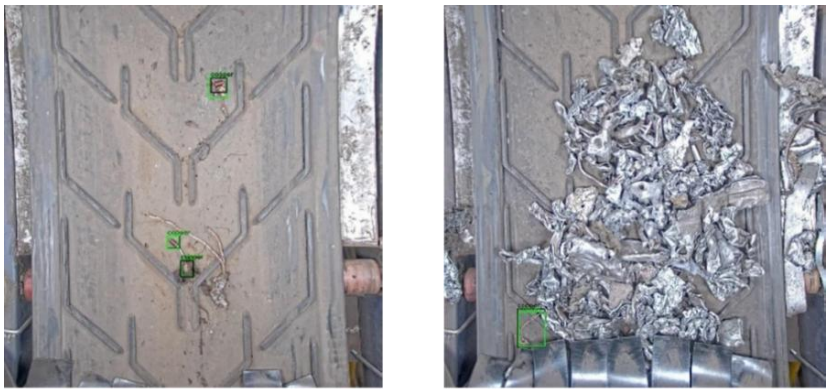

Fig.1 - Examples of true positive on Dataset 4.

3. CONCLUSIONS

This study presents a comprehensive evaluation of several object detection models trained on progressively larger and more diverse datasets to identify copper in the scrap to improve the quality of post-consumer scrap in the frame of PURESCRAP project.
During the project, the images for the object detection task were collected in different campaigns. In total, four datasets were created to assess the models' generalisation capabilities, particularly in real operating conditions. Two models architecture-based on Faster RCNN + ResNET 101 and YOLO were exploited and evaluated.

In general, the best performances in terms of mAP50 and FPS are achieved by YOLO model for all the datasets.
Work within the European PURESCRAP project is ongoing. Currently, the sensor station is being installed on Stena's production line. Then, information from the other installed sensors will be integrated to combine image processing and spectroscopic data (LIBS), enabling accurate analysis of the scrap composition.

ACKNOWLEDGMENTS
The work described in the paper was developed within the framework of Horizon Europe Clean Steel Partnership project, "Purity Improvement of Scrap Metal" (PURESCRAP – G.A. 101092168) which is gratefully acknowledged. The sole responsibility of issues treated in the paper lies with the authors; the Commission is not responsible for any use that may be made of the information contained therein.

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AI-BASED OPTIMIZATION OF COMPRESSED AIR NETWORKS IN HARD-TO-ABATE INDUSTRIAL SECTORS

Astolfi Giacomo, Luzi Francesco, Moscoloni Elena, Orlietti Lorenzo, Rosati Riccardo, Silenzi Andrea, Standardi Laura, Valzecchi Chiara – Alperia Green Future Srl, Italy

Decarbonizing hard-to-abate industries, such as steel, cement, and chemicals, requires boosting emission reductions and energy efficiency across as many parts of production plants as possible. Typically, systems dedicated to increasing energy performance in steel production plants mostly focus limitedly on furnaces.
This work illustrates an Artificial Intelligence (AI)-based system for the optimization of compressed air networks that are essential for driving sustainable industrial transformation. Such a system operates dynamically on pressure, moreover it also embodies anomaly detection and predictive maintenance. This innovative system not only enhances overall plant performance, but it also minimizes energy losses, reduces unplanned downtime, and extends equipment lifespan. The integration of AI-based control systems empowers end-users with actionable insights and autonomous optimization capabilities, translating into tangible cost savings and operational resilience.
Various applications of such AI-based system deployed to compressed air networks show up to 15% energy savings and a massive reduction in CO_2 emissions. These outstanding results demonstrate the strategic benefits of AI-based systems used in various industrial applications, supporting the broader goal of energy efficiency and sustainable industrial transformation.

KEYWORDS: STEEL – ARTIFICIAL INTELLIGENCE – COMPRESSED AIR – OPTIMIZATION – ENERGY SAVINGS – DATA ANALYSIS – MATHEMATICAL MODELING - EMISSION REDUCTION

AI-BASED OPTIMIZATION FOR HARD-TO-ABATE INDUSTRIES

In view of decarbonizing hard-to-abate industries, the focus has been mostly on specific areas of production plants such as furnaces and optimized scheduling of semi-finished casting products [1-4]. In these scenarios, real-time data are collected directly from production plants (**Fig. 1**). Thus, in-house software, fully tailored to customers' needs, deploys the latest AI algorithms to elaborate such data and compute optimal control signals aimed at boosting energy efficiency and plant performance. Furthermore, a fully customized HMI provides real-time plant KPIs and alarms if required. As this structure has been successfully deployed in many applications, results have shown massive reductions in energy consumption and CO2 emissions.

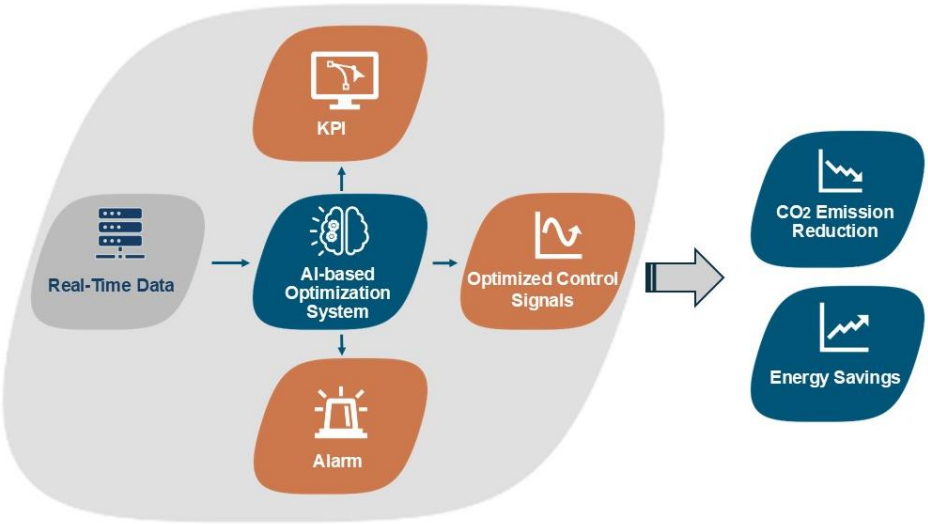

Fig.1 – AI-Based Optimization System Structure

COMPRESSED AIR-NETWORK

Compressed air-network is linked to compressors, and their energy consumption is typically significant, primarily due to their operation being often decoupled from actual production demands, resulting in inefficient usage and unnecessary power draw.
The proposed AI-based optimization system provides optimal control signals to compressors based on real-time data that designs actual and forecast production demands. Moreover, compressor performances are continuously analyzed, hence, predictive maintenance is enabled by such AI-based systems as well.
Current applications of such AI-based systems to compressed air-network have shown up 15% reduction in energy consumptions.

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AI-BASED SURFACE INSPECTION AND 3D PROFILING FOR QUALITY ASSURANCE IN STEEL PRODUCT GRINDING

Richard Sharp – Evertz Europe, Luxembourg
Jean-Louis Maurice – Evertz Europe, Luxembourg
Hannu Suopajärvi – Sapotech Oy, Finland
Saku Kaukonen – Sapotech Oy, Finland

High pressure grinding is gaining popularity and becoming the preferred surface conditioning method to remove defects from carbon steel semi-finished products. Compared to traditional scarfing, grinding offers several advantages, including higher flexibility of operations, optimized yield loss, easier and higher value recycling of the swarf, lower energy consumption and a reduced carbon footprint. To ensure that ground semi-finished products meet the stringent industry standards there is a need to apply automated analysis and measurement technologies.

This paper will present how an AI-based surface inspection system with advanced machine learning algorithms is used to identify surface anomalies in real time. This enables early detection and corrective actions to be taken, reducing material waste and improving overall process efficiency. Additionally, the integration of 3D profiling technology enhances quality control by accurately measuring the slab's surface geometry and topology. By using laser-based scanning, the system captures the complete slab profile with high precision, detecting deviations in thickness, flatness, and other critical geometrical dimensions.

KEYWORDS: SEMI-PRODUCT – SLAB CONDITIONING – GRINDING – AUTOMATIC SURFACE INSPECTION SYSTEM – 3D PROFILE MEASUREMENT

INTRODUCTION

Steel remains one of the cornerstones of modern society, enabling the construction and manufacturing of a huge variety of structures and products that are needed in everyday life. In 2024, steel production totaled 1 882.6 million tons [1]. Most of the steel is produced using continuous casting process technology whereby the liquid steel is continuously cast through a mould and the solidifying strand is pushed through the machine until it is cut into the desired length of the semi-finished product. The main semi-finished product types are slabs, billets and blooms.

Continuous casting is a mature technology, providing a means of efficiently producing a variety of different steel grades in vast quantities. Despite modern technologies including state-of-the art modeling tools and control software, the continuously cast semi-finished products possess surface defects, such as cracks, depressions, sticking defects, bleeders; all of which are detrimental to the quality of the final products.

Semi-product conditioning is needed after the continuous casting phase to ensure that the surface quality of the steel is defect-free, before releasing the product for further downstream processing. There are mainly two types of technologies used to remove surface defects from semi-finished products, namely scarfing and grinding. Scarfing is a treatment where an oxy-fuel torch is used to burn away (remove) a surface layer of the steel. Grinding is a mechanical process where abrasive wheels (grinding stones) are used to remove the same surface layer. High-pressure grinding is gaining popularity in the steel industry for a number of reasons; machine-tool repeatability, technology flexibility, optimized yield, improved process control, reduced energy consumption, lower CO_2 emissions, greener steel processing and improved surface integrity.

The combination of machine grinding, automatic surface inspection, and 3D measurement technologies enables a fully digitalized and controlled surface conditioning process, ensuring consistent product quality, precise defect removal, improved traceability, and increased operational efficiency across the production line. In this paper, the emphasis is to present the advantages of using automated surface inspection and 3D measurement in slab grinding.

HIGH-PRESSURE GRINDING

Industry shift from scarfing to grinding

Scarfing was historically the most common surface treatment method for carbon steel slabs. However, it is generally considered a cruder approach compared to machine grinding. With growing environmental pressure and concerns, many steelmakers are now shifting from scarfing to grinding.

Grinding offers significant advantages over scarfing, particularly in terms of performance and adaptability to digital technologies. It requires less energy and allows for direct collection and treatment of any emissions and dusts. Additionally, 100% of the material removed is easily collected and can be more efficiently recycled internally by the steelmaker, compared to the recycling of wet scarfing oxides.

The process is highly flexible - it can be applied to full-face, spot, corner, and edge grinding for various product types, including slabs, billets, blooms, ingots, and heavy plates. Grinding also presents lower operational risks due to its excellent reproducibility, elimination of reheating cracks, and short operator training time. Moreover, it does not require special licenses or permits and contributes to reduced CO_2 emissions.

Importantly, grinding can be fully integrated with online automatic 3D defect detection and process control, supporting the move toward digitalized “green” steel production. Despite these benefits, it is true to say today that most advanced machine grinding operations still rely on manual inspections from the operators, with limited use of modern machine vision or automated 3D detection technologies. Fig.1 compares the scarfing and grinding processes and the resulting surface finishes.

Fig.1 - Scarfing vs grinding

Principles of machine grinding

High pressure grinding is an abrasive method to remove material from the surface of the work piece. In steel semi-product grinding, the grinding wheel (or stone) made of abrasive materials and bonding agents is used to remove a layer of material as it moves back and forth over the work piece (slab). The main objective of the grinding is to remove the surface defects created during the casting process. The surface conditioning of the semi-products is of key importance. While ensuring a defect-free surface, the removal rate and processing time should be kept at a minimum to reduce yield loss and operational costs.

In an ideal world, slabs exiting the continuous caster would exhibit perfect surface quality. However, the reality today is that defects are inevitable, and surface conditioning becomes a necessity to improve the product quality. Given the stringent quality requirements for downstream processes such as rolling, coating, or forming, surface improvement through grinding is essential to ensure product integrity and process efficiency.

To grind slabs, the slab surface to be processed must be positioned in a worktable manner to enable the grinding stone to access the surface(s). Depending on the specific machine design, either the grinding machine moves over the slab (back and forth), or the slab itself translates back and forth beneath a fixed grinding unit. The material removal rate, throughput, and surface quality are influenced by key process parameters, including the type of grinding wheel, grinding speed, pressure/force, grinding angle, and feed rate.

The more powerful and productive slab grinding machines are typically based on a stationary grinding unit, and a moving worktable (See Fig.2). Slabs with known defects or programmed surface conditioning are typically transferred from the continuous caster by roller tables or overhead cranes. The slab is clamped on a moving worktable that moves the slab inside the machine and the grinding wheel is lowered down onto the slab surface. The worktable moves back and forth, and the system automatically performs the grinding according to the given preset parameters. The grinding head moves across the slab width in steps in the transverse direction so that the complete slab surface is processed. Once the top wide face of the slab has been ground, the grinding wheel rises, and the worktable moves the slab out from the grinding enclosure to the turntable. The slab is turned, after which it returns inside the grinder to be symmetrically ground on the other face. [2] Different machine designs and configurations are possible in order to grind the long slab edges and corners.

Fig.2 - Heavy slab grinding machine

The less powerful grinding machines designed and manufactured by Evertz feature a moving grinding unit and a stationary worktable (See Fig.3). While traditionally used for billet and bloom grinding, this type of machine is now also widely applied to slab grinding. In earlier designs, the operator pulpit was integrated into the moving (translating) grinding unit. In recent designs, the pulpit is separated and delocalized from the grinding machine itself, enabling the control and operation of two or more machines from a single operator pulpit.

Fig.3 - Standard slab grinding machine

Traditional product quality assurance

As already stated, slab grinding criteria and quality assessment have traditionally relied on predefined "rule books" and manual quality inspections. Based on the work undertaken by Piippo [2] each steel grade should have its own grinding criteria, and many different grinding programs should be used according to numerous factors. The choice of which grinding program is determined by the casting parameters, steel grade, resultant slab quality after casting and the final product application/destination. If residual defects remain after using the predefined grinding program, spot grinding using the machine can be undertaken.

The traditional way of conducting surface inspection after full face grinding is labor-intensive, prone to human error and generally leaves no recorded traceability (once the slab goes on for further transformation). In this case, the operator needs to leave the pulpit (or machine) in order to physically see the slab post grinding and visually inspect the full slab surface. Since the slab can be over 10 000 mm long and 2 400 mm wide, a detailed inspection of the complete surface proves to be a challenging task and of course takes time. The heavy industrial environment, lighting, temperature and overall working conditions do not make this an easy task.

MATERIALS AND METHODS – AI-BASED SURFACE INSPECTION AND 3D-BASED PROFILING

Reveal CAST design for slab grinding

The main target of an automatic surface inspection system for the grinding process is to enhance the performance of the surface conditioning undertaken by providing the operator(s) with a tool that will assist in locating the surface defects quickly and accurately to decide what conditioning is required. It also acts as a tool to log and record the ground surface quality for future requirements. Designing an optical system for the inspection of ground slab surfaces presents significant challenges due to the highly reflective, patterned, and non-uniform surface texture of ground steel. The surface properties can interfere with accurate image acquisition and automatic defect detection. Furthermore, the harsh industrial environment characterized by high temperatures, vibration, dust, and mechanical hazards necessitates implementation of robust protective measures to ensure system durability, stability, and long-term reliability in continuous operation.

Sapotech has developed, with the support of Evertz, a 2D inspection system called Reveal CAST that can be applied on slabs, billets and blooms of any size [3]. Consisting of several cameras to ensure high resolution images and multiple LED units for consistent illumination, the system is today able to capture sharp images with 150 µm resolution from wide (up to 2 400 mm) slabs. The optical and mechanical design of the system must be carefully engineered to deliver high-resolution and stable imaging under harsh industrial conditions. It must combine robust protective housing, cooling, vibration resistance, precise sensor alignment and enable reliable inspection across a wide product range.

In addition to image capturing, the development of image processing, data handling and database approaches has required extensive development work. The server infrastructure design to run Deep Learning algorithms has been one of the requirements to advance in fast surface analyses. Consisting of several NVIDIA based Graphics Processing Units (GPUs), the developed multilayer neural network models can detect and classify multiple defect types in seconds.

3D profile measurement development for slab grinding

To replace manual, random dimensional inspections of slabs performed using calipers or micrometers, Evertz and Sapotech initiated a study into the development of an automated measurement system employing 3D laser profile sensors. Due to the substantial width of the slabs, it was evident from the outset that achieving the required measurement accuracy across all three spatial dimensions (X, Y, and Z) would necessitate the integration of multiple sensors with high resolution and fast scanning capabilities.

After supplier evaluation, the selected 3D sensor was trialed in a real industrial environment by mounting the equipment to the grinding machine body and making preliminary scans with the sensor. After a successful first trial and validation of the measurement results compared to manual measurements, the optimum sensor type was selected as a basis for solution development.

Three 3D sensors and a network controller were acquired for system development. To enable integration with the grinding machine, custom protective housing was designed and manufactured. In addition to the 3D sensors, the housing also accommodates Reveal CAST sensors (Fig.4). Since the system scans the slab surface before and after each grinding pass, protective flaps were incorporated into the bottom of the housing. The optical path to the slab is exposed only during scanning. At all other times, the flaps remain closed to shield and protect the equipment from sparks, dust, and other contaminants.

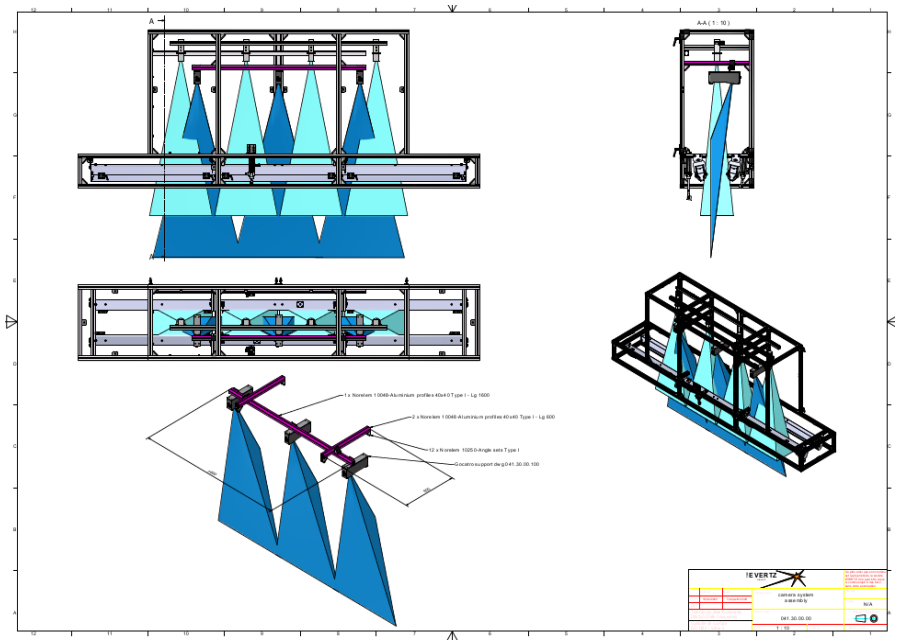

Fig.4 - 3D sensor and Reveal CAST equipment inside the sensor box (shielding not shown above)

Multi-sensor integration and sensor calibration turned out to be quite straightforward because of the built-in functions within the sensor software. To be able to correlate 3D scans with grinding machine position an encoder was installed and connected with the scanning system. 3D scanning of the slabs results in massive data generation. The data is pretreated on a sensor and further processed in the servers. The measurements based on laser triangulation approach will be integrated with the Reveal CAST automatic surface inspection system (ASIS). All the detections and measurements are visualized in the Reveal CAST user interface.

RESULTS

Reveal CAST results for slab grinding

The installed Reveal CAST SIS conducts surface inspection of cast and ground slabs. High-resolution images captured by LED illuminated area scan cameras are preprocessed and stitched to create full slab images. The core of the automatic defect detection system is a U-Net convolutional neural network trained for semantic segmentation. It processes preprocessed image tiles to identify and localize surface defects at the pixel level. The model outputs include the defect class (e.g., crack, inclusion, porosity …), precise defect boundaries, and a confidence score for each prediction. Image inference is performed on a centralized GPU server cluster, which allows for scalable and efficient batch processing of large image sets. The system is optimized for near real-time performance, balancing accuracy and processing speed to meet production requirements.

Detected defects are visualized in the user interface through overlays on the original slab images (Fig.5). Operators can inspect defects in detail using zoom and navigation tools, while also accessing summaries such as defect count, size, and distribution across the slab. All results are logged into a central database, linked to slab metadata for full traceability. This historical data can be retrieved for quality reporting or process improvement any time in the future. In addition, the system can forward key results to external systems such as MES or automatic grinding control, enabling real-time process adjustments or defect-driven actions.

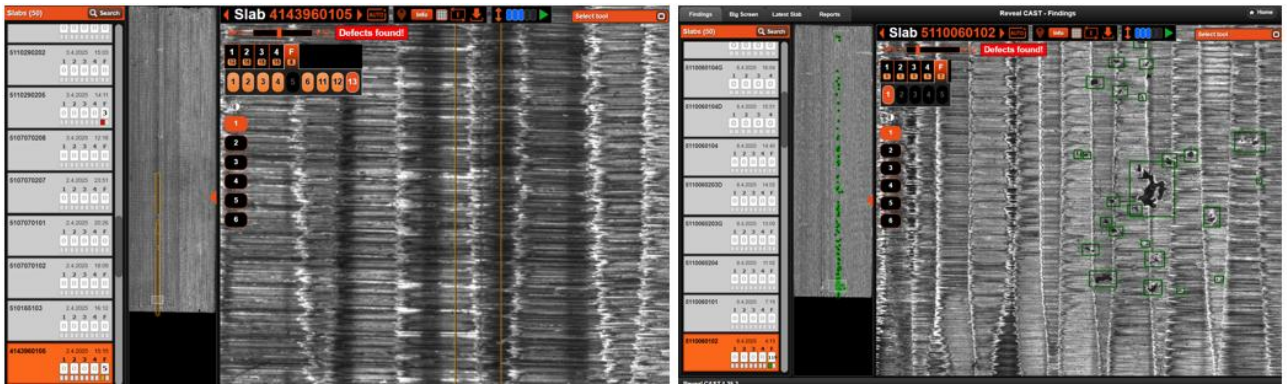

Fig.5 - Reveal CAST user interface with detected defects

The Reveal CAST surface inspection system has been successfully used in Evertz grinding machines for several years, providing extensive operational experience. Tab.1 presents the benefits the system offers in everyday use.

Tab. 1 - Benefits of using Reveal CAST system in slab grinding.

BENEFITS OF USING REVEAL CAST SYSTEM IN SLAB GRINDING	
Improved Grinding Efficiency	The system significantly enhances grinding efficiency by automating defect visualization and detection, greatly reducing the need for manual inspection. This results in faster processing compared to previous practices. Thanks to high-resolution imaging, operators no longer need to leave the control room to physically verify defect severity—this can now be done directly through the Reveal CAST user interface. As a result, overall process throughput has improved.
Enhanced Final Quality and Yield	The final quality of ground slabs has improved since the implementation of the system. Previously, physically inspecting every inch of a ground slab with high precision was impractical; Reveal CAST now makes this possible. Yield improvements have been observed for certain steel grades, but more importantly, surface quality has become more consistent even if it occasionally requires additional grinding to ensure defect-free results.

Optimized Grinding Routine and Process Development	Reveal CAST enables automatic spot grinding by providing precise defect detection. Real-time imaging also provides early indications of potential issues with the grinding stone or process parameters. This allows operators to take corrective actions immediately, ensuring process stability and consistent grinding performance.
Improved Reporting and Traceability	Traceability of conditioned slabs has improved considerably. Since the system's deployment, it has been possible to provide detailed documentation of surface quality upon exiting the grinding process - valuable information, especially for service providers working with end customers. Surface images and associated analysis data are stored for several months and can be retrieved whenever needed for quality verification or process review.

3D measurement results

A wealth of information can be extracted from the measurement data, as the 3D sensors capture the full surface profile of the slab. The first Key Performance Indicator (KPI) derived from this data was the material removal rate — a critical metric for verifying that sufficient material has been removed to eliminate surface defects.

First, the slab - bearing the "rough" surface from the continuous casting process - is scanned using the profile measurement system. After surface grinding, a second 3D scan is performed on the treated surface. The acquired data is visualized in the user interface as a 3D surface map (see Fig. 6), and all measurements are stored for further analysis.

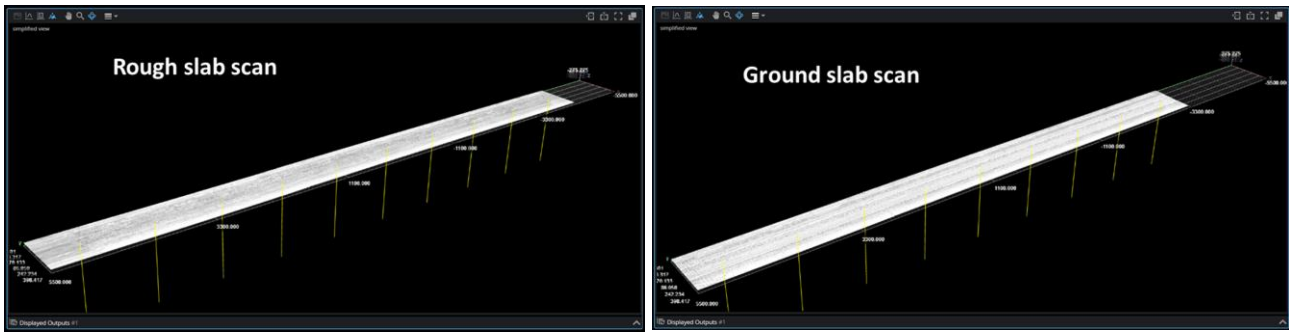

Fig.6 - Rough slab scan (on the left) and ground slab scan (on the right)

The material removal rate is determined by comparing Z-axis values before and after grinding at defined X–Y positions. The difference in Z-values directly corresponds to the amount of material removed. Tab. 2 provides an example of this calculation. Measurement points are collected at one-meter intervals along a specified X-axis line, with the first Y-position located 350 mm from the slab head.

In this example, measurements were demonstrated along a single line; however, the system is fully capable of capturing Z-values at all measured X–Y coordinates if required. The calculated removal rates were validated against manual measurements, showing excellent correlation between the two methods. Based on multiple validation results, the customer has already approved the laser-based material removal measurement approach as a reliable replacement for manual measurements. Combined with Reveal CAST ASIS, the 3D profile measurement ensures that only the minimum amount of material is removed whilst ensuring all the surface defects have been eliminated.

Tab. 2 - Material removal

MATERIAL REMOVAL				
	Distance from slab head [mm]	Z position Rough slab [mm]	Z position Ground slab [mm]	Diffference [mm]
Pos 1 / Z	350	-367,595	-370,923	-3,328
Pos 2 / Z	1350	-367,964	-371,105	-3,141
Pos 3 / Z	2350	-365,523	-368,510	-2,987
Pos 4 / Z	3350	-362,549	-365,631	-3,082
Pos 5 / Z	4350	-361,361	-364,273	-2,912
Pos 6 / Z	5350	-361,707	-365,237	-3,53
Pos 7 / Z	6350	-368,119	-371,127	-3,008
Pos 8 / Z	7350	-368,911	-372,265	-3,354
Pos 9 / Z	8350	-367,613	-370,661	-3,048

Several other applications for the 3D profile measurements have already been planned. For example, after scanning the slab with rough surface before grinding, it may be possible to adjust the grinding depth, pressure or pass count based on the slab profile and condition.

CONCLUSIONS AND FUTURE OUTLOOK

Conditioning of semi-finished products is a vital step in steel production to ensure high-quality, defect-free final products. Slab grinding is increasingly preferred over traditional scarfing due to its superior precision, improved safety, and lower environmental impact.

This paper has shown how the grinding process can be further enhanced through the integration of modern measurement technologies. The Reveal CAST Automatic Surface Inspection System enables reliable detection and classification of surface defects, ensuring targeted and efficient material removal. In addition, 3D profile measurements provide accurate data on material removal rates, supporting improved material efficiency by minimizing steel loss, reducing grinding stone consumption, and lowering energy consumption.

Future development will focus on deeper integration of the Reveal CAST with 3D profile measurement technology, enabling full digital traceability of both surface appearance and geometric features. This integration allows for correlated and overlaid 2D defect maps with 3D topography data, creating a high-fidelity digital twin of each slab.

ACKNOWLEDGEMENTS

The “Innovative integration of high precision laser measurements, artificial intelligence based surface analysis and predictive process models” (InToSteel) project (S0625) has received funding from Luxembourg Ministry of Economics and Business Finland through Eureka and SMART Clusters program.

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Local Area Production System

Jan Thiel – PSI Software SE,
Dircksenstraße 42-44, 10178 Berlin, Germany

The Manufacturing Execution System as a Central System Integrator

A central Manufacturing Execution System (MES) serves as a reliable and trusted single source of truth for production and material tracking. As the core system, it integrates all automation systems, Enterprise Resource Planning (ERP), and Quality Systems. However, while this centralized approach offers numerous benefits, it also presents certain challenges. The unavailability of a central MES can be critical, potentially leading to a complete production stoppage, as line automation often relies on a constant data supply. In addition to the risk of unplanned downtime, scheduling maintenance, updates, or extensions can also be problematic. Although some production areas may have multiple planned downtimes for machinery maintenance, typically, there is only one planned downtime for the entire site each year. Moreover, integrating many heterogeneous systems adds significant complexity to the MES, increasing the need for more frequent updates and maintenance.

Increasing Flexibility and Security with Local Area Production Systems

The introduction of Local Area Production Systems (LAPS) can enhance flexibility and security while simplifying the central MES without sacrificing its advantages. A LAPS integrates with the automation of specific production areas, such as the hot rolling area, and manages production tracking. It receives production orders, materials, and schedules from the central MES and reports production results. While the MES remains the single source of truth for production tracking across the entire process chain, it no longer needs to integrate with numerous heterogeneous line automation systems. Instead, it connects with a reduced number of Local Area Production Systems through a defined standard interface, simplifying MES standardization and facilitating easier system upgrades.

LAPS empowers line operators to independently manage production for a designated period, utilizing a backlog of schedules, materials, and production orders. This ensures continuity even if the central MES or other tracking systems are impaired or offline. Additionally, it allows for the scheduling of MES updates and maintenance without necessitating planned downtime for the production site. If a LAPS requires updates—such as extensions to the line automation interface—these can be scheduled during a maintenance slot for the production area without impacting other areas.

LAPS streamlines production by overseeing line sequences, material tracking, and post-production tasks like weighing, sampling, and inspection. It equips operators with all the necessary tools to respond to unplanned production events e.g. enabling reactive adjustments to line schedules.

LAPS as Enablers for System Renewals and Software as a Service

In addition to the benefits outlined above, Local Area Production Systems can address two significant challenges in production management systems. The first challenge is the renewal of an obsolete MES. A "big bang" replacement carries substantial risks. A more strategic approach would be to introduce one LAPS for a specific area at a time, initially integrating it with the old MES. The Local Area Production Systems gradually take on the complexity, thereby mitigating risk. Ultimately, a streamlined new MES can be connected to the LAPS that have already proven effective in production.

The second challenge involves integrating a cloud based Software as a Service (SaaS) MES with time-critical local automation systems. On-premise Local Area Production systems can act as buffers, facilitating connections to a SaaS MES.

PSI Software SE will introduce LAPS as part of the PSI Service Platform.

KEYWORDS: LAPS - MES - PRODUCTION TRACKING - AUTOMATION INTEGRATION - SYSTEM MAINTENANCE - SOFTWARE AS A SERVICE

Smarter Galvanizing through Zinc Coating Optimization with EMG iCASS®: A Modular AI-Driven Platform

Mark Kreso, Anno Jordan, Sven Johnson, Stefan Weber, Robin Weinreich – EMG Automation GmbH,

In hot-dip galvanizing, achieving precise zinc coating thickness while minimizing material use is a persistent challenge. Traditional control methods often respond too late due to delayed measurements, especially during strip transitions. EMG iCASS® (intelligent Control and Analytical Software Solutions) addresses this with a modular, AI-powered platform for real-time process optimization in continuous galvanizing lines (CGLs). It uses machine learning models and predictive analytics to dynamically adjust process parameters based on historical and live data. Key modules include the Virtual Hot Measurement, which forecasts coating thickness right after strip changes, and the Safety Margin Adjustment, which reduces excess zinc while preventing undercoating. The Nozzle Position Optimization ensures transverse coating uniformity, and the Real-Time Coating Control module actively controls the air knife parameters for consistent quality and targeted coating thickness. Industrial trials confirm EMG iCASS® as flexible, scalable architecture which makes it a future-proof solution for data-driven steel production.
The platform enables faster adaptation to production changes and reduces reliance on expensive and less reliable radiometric hot measurement systems. The modular concept allows phased deployment based on use-case priority and existing infrastructure.

KEYWORDS: REAL-TIME PROCESS CONTROL – MACHINE LEARNING – ZINC COATING OPTIMISATION – PRESCRIPTIVE ANALYTICS – HOT MEASUREMENT – VIRTUAL SENSORS – CLOSED-LOOP CONTROL

INTRODUCTION

In the age of Industry 4.0, metal strip production processes—such as steel rolling and hot-dip galvanizing—face growing demands for quality, efficiency, sustainability, and cost reduction. Customers expect uniform mechanical and surface properties, while producers aim to reduce material consumption and minimize waste. At the same time, industrial production lines generate vast amounts of process and quality data that are often underutilized. Traditional control methods in these settings typically rely on fixed parameter sets and sometimes delayed measurements, making them reactive rather than predictive. Adjustments to process parameters are often carried out manually or based on empirical knowledge, which limits the ability to adapt dynamically to changing material conditions or production targets.

To address these challenges, there is a pressing need for intelligent solutions that harness the power of real-time data analytics, machine learning (ML), and advanced control systems. These solutions must be flexible enough to operate in heterogeneous production environments and robust enough to integrate seamlessly with existing equipment and software systems.

EMG Automation GmbH has responded to this need by developing EMG iCASS® (intelligent Control and Analytical Software Solutions), a modular and scalable platform that transforms process and quality data into actionable insights. Designed specifically for metal strip production lines, EMG iCASS® combines classical automation with state-of-the-art analytics and artificial intelligence techniques to optimize process performance in real time.

The EMG iCASS® platform has been developed as part of a collaborative industrial R&D initiative between thyssenkrupp Steel Europe (tkse), EMG Automation GmbH, and NeurologiQ, an AI specialist. A key outcome of this collaboration is the implementation of machine learning models for real-time control of hot-dip

galvanizing processes [1]. In the joint project, a production line of tkse equipped with the EMG eMASS® strip stabilization system and DUMA-BANDZINK air knife technology demonstrated how AI-driven models can predict zinc coating thickness and generate real-time pressure setpoint recommendations for the air knives with response times under 100 milliseconds. This application exemplifies the predictive and prescriptive capabilities of the EMG iCASS® framework.

The aim of this paper is to present the EMG iCASS® platform, outline its system architecture, demonstrate the data analytics methods it employs, and provide validated examples of its application in industrial galvanizing processes. Through these insights, the paper aims to illustrate how intelligent software platforms can drive digital transformation and operational excellence in the metal processing industry.

EMG iCASS®: CONCEPT AND ARCHITECTURE

EMG iCASS® (intelligent Control and Analytical Software Solutions) is designed as a modular, scalable, and highly integrative platform that enables advanced data-driven control and optimization of industrial production lines. At its core, EMG iCASS® is a software-based system that bridges the gap between sensor-level data acquisition, PLC-level process control, and high-level production management systems such as MES (Manufacturing Execution Systems). By directly interfacing with PLCs, EMG iCASS® can actively influence process parameters in real time, enabling closed-loop control and dynamic optimization.
The architecture of EMG iCASS® is built to support heterogeneous data environments and varying automation levels found in steel strip processing. It connects to a wide range of field devices, including process sensors, actuator controllers, and inline measurement systems, ensuring comprehensive data collection in both temporal and spatial resolution. Typically, several hundred or more input signals and process variables can be recorded per production line, often at millisecond-level resolution.

The platform uses a layered approach:

- **Data Acquisition Layer**: Interfaces with sensors and PLCs to collect real-time process data, such as strip speed, temperatures, pressures, coating thickness, material grades, and actuator settings.
- **Data Management and Storage**: Efficient structuring and secure storage of high-resolution time series data to support traceability, offline analysis, and model training.
- **Analytics and Modelling Layer**: Provides the foundation for advanced analytical applications, including machine learning model deployment, statistical evaluations, and visual analytics.
- **Control and Integration Layer**: Enables closed-loop control functionalities by interfacing back to PLCs and control systems, allowing real-time adaptation of process parameters based on insights generated.

The modular design of EMG iCASS® makes it adaptable to both partial deployments (e.g., for offline analysis or monitoring only) and full integration into live control loops. Each module can be customized or scaled independently, depending on customer needs, available infrastructure, and digital maturity.
In terms of system integration, EMG iCASS® is engineered for interoperability. It supports standard industrial communication protocols and data formats to interface seamlessly with existing systems. This makes it suitable not only for new installations but also for retrofitting into existing lines without requiring major hardware changes.
Overall, EMG iCASS® establishes a digital backbone for intelligent process control and serves as a key enabler for advanced use cases such as predictive quality, anomaly detection, prescriptive optimization, and continuous process improvement in strip processing environments. Fig. 1 shows the principal architecture of the EMG iCASS® platform for the example of the hot dip galvanizing process.

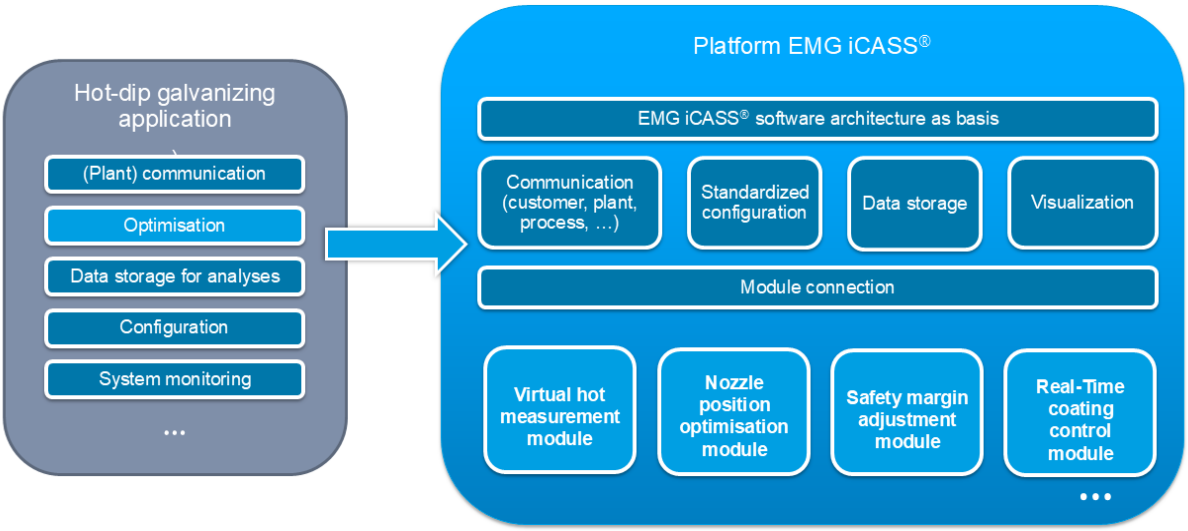

Fig. 1: Basic architecture of the EMG iCASS® platform

The figure provides a structural overview of how the EMG iCASS® platform integrates with hotdip galvanizing applications. On the left, key application-level functionalities are shown, including plant communication, optimisation, data storage for analysis, configuration and system monitoring. These tasks form the context in which EMG iCASS® operates.
On the right, the architecture of the EMG iCASS® platform is presented as a layered software environment. At its core it is a standardized software framework that includes communication interfaces (customer, plant, and process-level), configuration tools, centralized data storage, and visualization capabilities. These foundational services support the platform's role as a data and control backbone. Beneath the architecture layer, the platform connects to a suite of specialized modules through a standardized module connection layer.

FROM DATA TO INTELLIGENCE: MACHINE LEARNING FOR PROCESS OPTIMISATION

In steel and other metals strip production, the availability of high-resolution data from sensors and automation systems opens up new possibilities for advanced process analysis and control. EMG iCASS® leverages this data foundation by systematically applying data science methodologies and machine learning (ML) to transform raw signals into actionable intelligence.

The analytics journey typically begins with correlation analysis. This step explores relationships between process parameters (e.g., temperatures, strip speed, air knife pressure) and quality results (e.g., zinc coating thickness, homogeneity in various tracks). It helps identify relevant input features and eliminate redundant or noisy signals, forming the basis for model development.

Next, predictive modelling is employed. Here, supervised learning algorithms are trained on historical datasets to forecast key output variables such as coating thickness or mechanical properties. These models can anticipate process outcomes for new coils and serve as virtual sensors in areas where direct measurement is technically or economically unfeasible. One example is the "Virtual EMG IMPOC", which estimates material strength values based on online process data and historical tensile test results.

As a further step, EMG iCASS® enables the implementation of prescriptive analytics. This most advanced level of data-driven decision support not only predicts outcomes but also recommends or directly executes optimized process settings. For instance, in hot-dip galvanizing, machine learning models trained on historical coating and process data can generate real-time setpoint recommendations for the air knife system. These setpoints are transmitted back to the PLC with response times well below 100 milliseconds, enabling closed-loop control without hot measurement devices.

The implementation of prescriptive analytics in EMG iCASS® follows -independently from the application case - a structured three-stage methodology (Fig. 2):

1. **Modelling:** Predictive models are developed using historical process and quality data. These models estimate e.g. zinc coating thickness based on parameters like strip speed, furnace temperature, air knife pressure, and material composition.

2. **Optimisation:** This stage consists of two critical software components:
   The Optimiser calculates e.g. forecast zinc layer values for various potential combinations of control variables in real time, using the trained models. In the pilot application at tkse this control parameter was the air knife pressure.

   The Arbiter selects the most suitable set of control parameters from the simulated alternatives to meet the target coating thickness, considering quality requirements and efficiency constraints.

3. **Control:** The selected control setpoints are delivered back to the line in real time. The process line (via the PLC) adjusts its parameters accordingly, closing the control loop and e.g. enabling dynamic, optimal galvanization.

To ensure robustness and reliability, all models in EMG iCASS® undergo rigorous training, validation, and verification phases. They are continuously monitored in live environments and can be retrained with newly available production data, supporting long-term model adaptation and learning.

Overall, the transition from descriptive to prescriptive analytics marks a significant step toward autonomous process optimization [2]. By embedding machine learning into the control architecture, EMG iCASS® empowers production teams to make faster, more precise, and data-driven decisions, thereby improving product consistency, reducing material waste, and enhancing overall line performance.

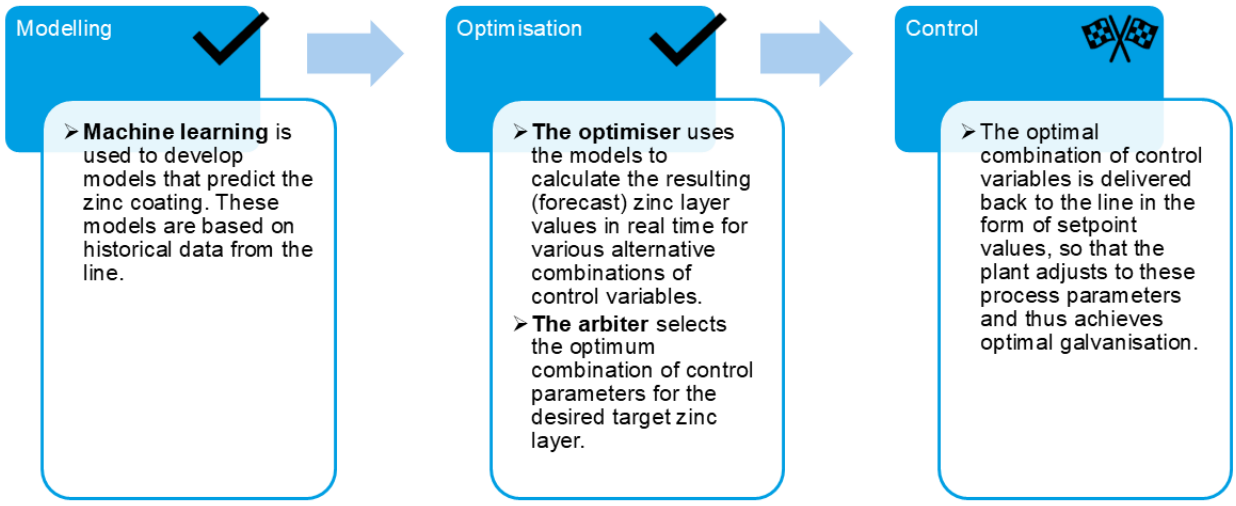

Fig. 2: Three stage methodology to achieve real-time control based on EMG iCASS®

EMG iCASS® MODULES AND INDUSTRIAL APPLICATION IN HOT-DIP GALVANISING

The modular structure of EMG iCASS® as described in the chapter: EMG iCASS®: CONCEPT AND ARCHITECTURE, allows for targeted implementation of functionality to address different challenges. In this paper the hot-dip galvanising process serves as a role model for similar challenges in the production of flat metal process. Each module is designed to solve a specific optimization problem and can operate independently or as part of a larger integrated control strategy. The flexibility of this architecture enables users to focus on the areas of greatest impact based on the line configuration, process conditions, and quality objectives.

Virtual Hot Measurement / Strip transition module

This module predicts zinc coating thickness immediately following strip transitions or changes in material and coating target values. Traditional hot measurement systems, which are based on radiometric measurements, present a number of challenges. They require frequent maintenance and special handling with regard to radiometric sources. They are also highly sensitive to variations in strip distance and only deliver readings from a single measurement track. These systems are often unable to deliver reliable results for the first 60–150 metres of a new strip as warm or cold measurement data only become available later. The model-based approach in EMG iCASS® offers a predictive alternative. This ensures continuity of quality control. It starts directly / immediately from the very beginning of the strip. Relying on historical coating and process data, it calculates expected values per track and side, significantly reducing scrap and improving responsiveness during production changes.

Fig. 3 illustrates a typical production scenario where the EMG iCASS® Virtual Hot Measurement Module is applied to predict zinc coating thickness on the upper side centre track of the strip. The time-series chart compares three datasets:

- **Red**: Cold measurement values of the zinc coating from the upper side centre track.
- **Blue**: Predictions generated by the machine learning model used in the virtual hot measurement module.
- **Green**: Hot measurement values (used here for benchmarking but not included in model training).

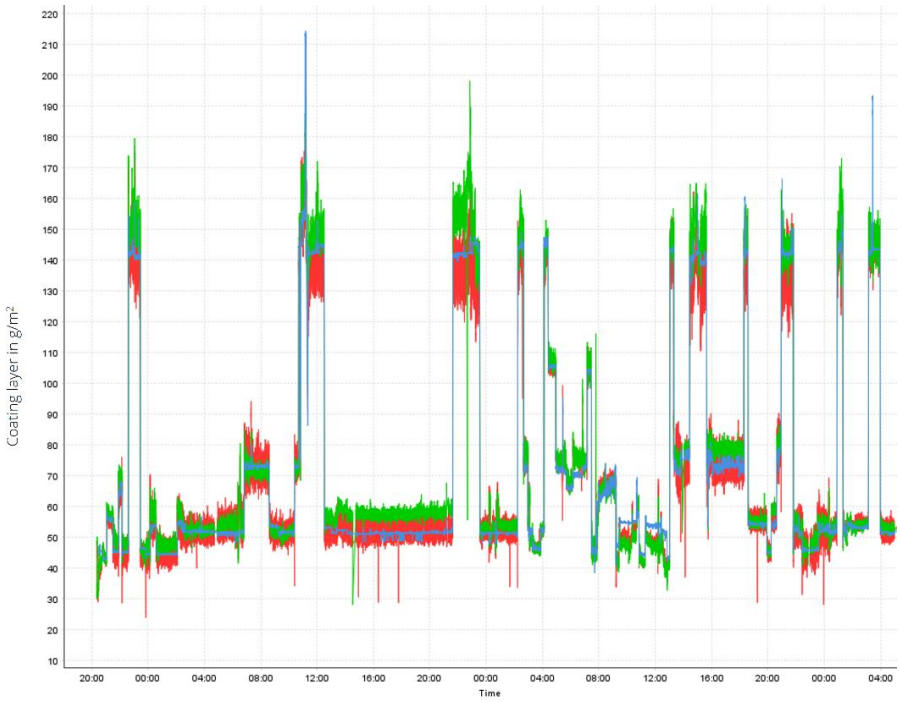

Fig. 3: Performance of the virtual hot measurement module in real production over a set of subsequent coils. Blue: predictions by EMG iCASS®, Green: hot measurement, Red: Cold measurement

The graph demonstrates that the predictive model shows excellent agreement with the cold measurement values and exhibits forecast accuracy equivalent or better compared to the hot measurement at this production line. Importantly, the model was trained without using hot measurement data, relying solely on historical process and quality data. This confirms the capability of the EMG iCASS® solution to deliver accurate coating forecasts even in environments where hot measurement is unavailable or unreliable. The model supports predictions for multiple tracks (in this case, three but more are possible), enabling improved spatial resolution of coating control.

Safety Margin Adjustment module

This module helps minimize zinc overcoating while safeguarding against undercoating. It offers two modes:

- **Static optimization**, which determines fixed margins per coil and material group.
- **Dynamic optimization**, which adjusts the safety margin in real time based on process stability and coating variability over strip length. By adapting safety margins to actual process performance, the module reduces material usage without compromising customer specifications—particularly important for single spot test (SST) coils.

Fig. 4 illustrates the dynamic optimization potential of the EMG iCASS® Safety Margin Adjustment Module. It shows a typical production sequence where the coating is optimized according to customer specifications (SST).

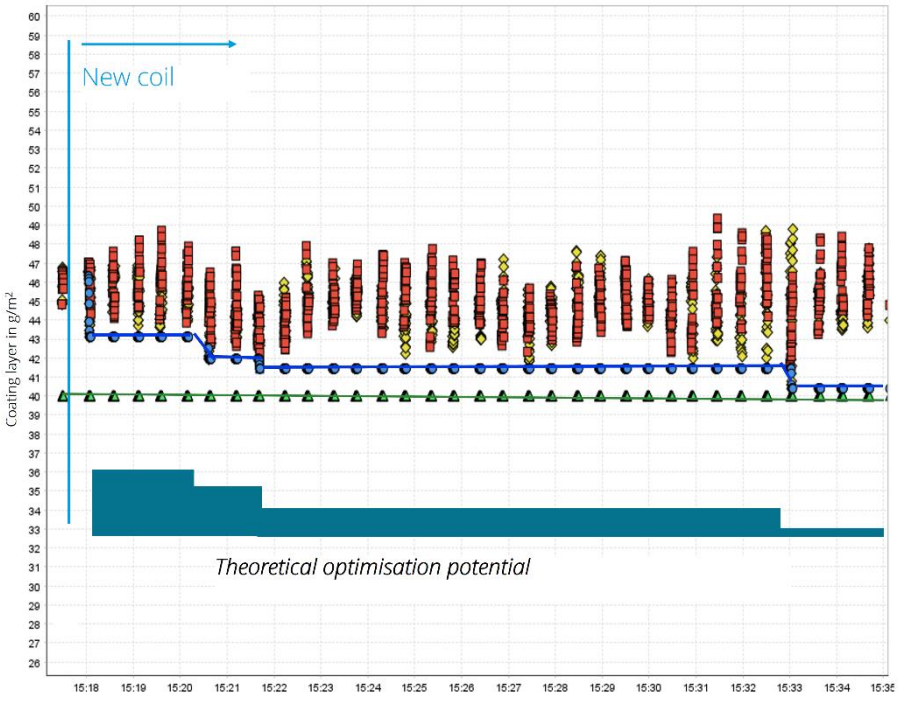

Fig. 4: Dynamic safety margin optimisation in practice

- **Red and yellow markers** indicate the actual top and bottom side coating measurements.
- **Blue line** represents the minimum zinc coating measured across the strip.
- **Green line** reflects the specified target coating layer.

In the beginning the minimum coating layer (blue) remains significantly above the target value (green), indicating an unnecessarily high safety margin in the beginning. This visualizes the theoretical optimization

potential: through real-time adjustments based on coating stability and process behaviour, the module enables reductions in excess zinc application.

Such dynamic margin control allows for continuous fine-tuning of zinc usage over the strip length. The result is better material efficiency without risking undercoating, contributing to significant cost savings in zinc consumption.

Nozzle Position Optimisation module

In galvanising lines equipped with an EMG eMASS® system, this module determines the optimal alignment of the air knife relative to the strip. It adjusts the positions of the nozzles to eliminate wedge-shaped coatings and improve transverse homogeneity. Another function is the automatic equalisation of coating thicknesses on the top and bottom of the strip. These functions improve the effect of EMG eMASS® strip stabilisation and help the strip stabiliser to eliminate crossbows or other strip shapes further during the coating process. This is particularly important during the production of SST-relevant strips.

Fig. 5 illustrates the principle behind nozzle alignment corrections performed by the EMG iCASS® Nozzle Position Optimisation module. It shows three schematic representations of zinc coating distributions across the strip width:

- **Top left (Zinc coating with wedge shape)**: A misaligned nozzle results in an uneven coating profile, where the top and bottom side coatings differ across the strip (typically thicker on one edge).
- **Bottom right (Zinc coating shifted in parallel)**: A consistent offset in coating thickness across the strip width, indicating a lateral displacement of the nozzle.
- **Centre (Ideal zinc coating)**: A uniform, centred coating profile achieved through optimal nozzle rotation and/or parallel displacement as optimum starting point for electromagnetic strip stabilisation with EMG eMASS®.

  The diagram also highlights the two corrective actions:

- **Nozzle rotation**: Adjusts angular misalignment to flatten wedge-shaped coatings.
- **Parallel displacement**: Shifts the nozzle laterally to re-centre the coating distribution.

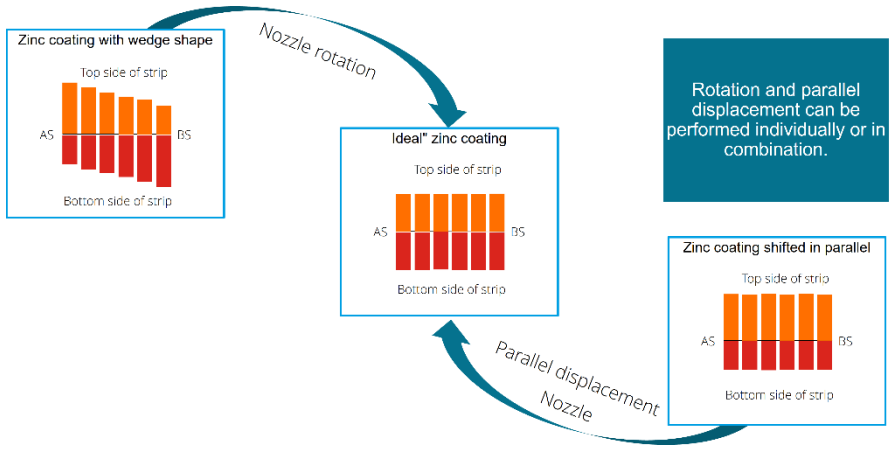

Fig. 5: Concept of nozzle rotation and parallel displacement correction for CGLs with EMG eMASS®

Real-Time Coating Control module

This is the most advanced module, enabling closed-loop control of zinc coating thickness based entirely on machine learning models and real-time data. It replaces the need for manual setpoint adjustment and conventional model-based control logic. The system reacts to changes in input (e.g. speed, various process

temperatures, geometric parameters and coating target) by providing low-latency recommendations for setpoints, pressure and, if required, nozzle position and other variables, thereby ensuring optimal coating thickness throughout the coil and cross web.

Fig. 6 illustrates an exemplary production sequence where the EMG iCASS® Coating Control Module is actively managing the zinc coating process in a closed-loop configuration with the pressure as control variable. The time series visualizes the module's performance by plotting multiple key process variables:

- **Blue and red lines**: Actual coating measurements on the upper and bottom side of the respective coil
- **Thick black line**: Minimum zinc coating requirement according to end customer specification
- **Orange line**: Strip speed
- **Light blue line**: Distance between the air knife and the strip (kept constant in this example)
- **Green line**: Air knife pressure

The data demonstrates how the EMG iCASS® module adjusts control parameters in real time to maintain coating within specification. For instance, at approximately 20:08, the system automatically increases pressure in order to reach a lower coating weight. In the beginning of this coil the pressure selected was somewhat too high to guarantee the safety margin for SST-testing and therefor it was reduced afterwards.

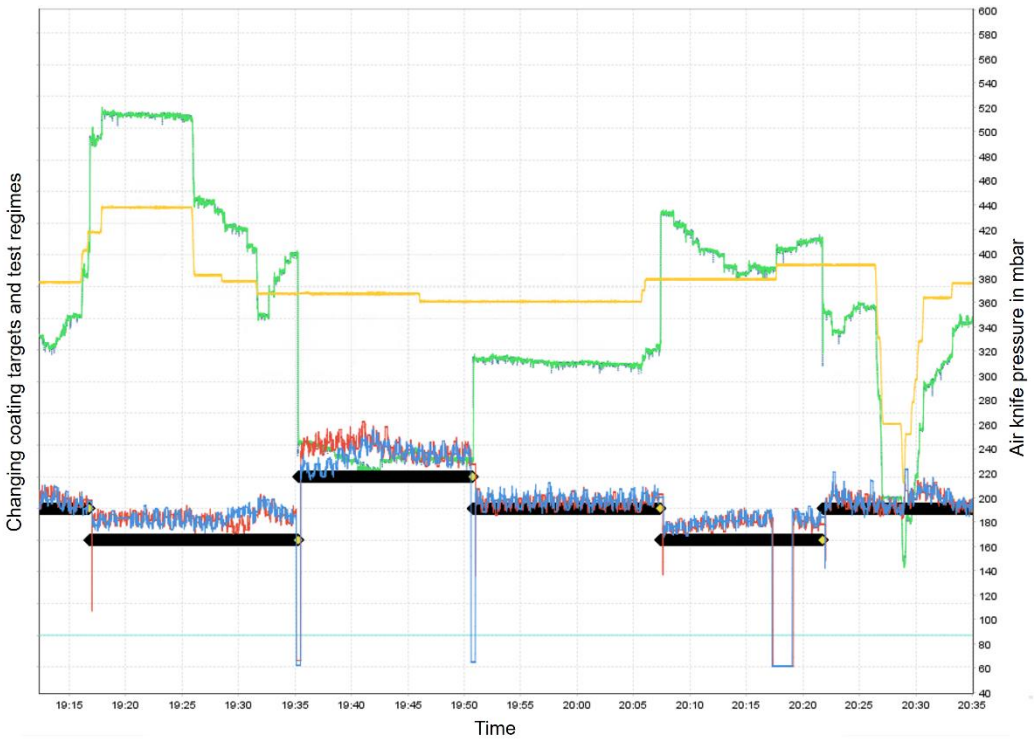

Fig. 6: Closed-loop control of coating in a CGL: exemplary production sequence

The production sequence includes multiple transitions between different coating targets and testing regimes in the following sequence: 1. triple-spot-test (TST) → 2. single-spot-test (SST) lower coating target → 3. SST higher coating target → 4. TST somewhat lower coating target → 5. SST same coating target as 2. → 6. TST same coating target as in 1.

These transitions show how the system dynamically responds to changing requirements without operator intervention. This example confirms the module's ability to provide low-latency, model-based process control and highlights the value of integrated AI in achieving consistent, high-quality production while minimizing

overcoating and manual workload.

Together, these modules demonstrate how EMG iCASS® can be tailored to specific operational goals—from process stability to cost efficiency—while providing a robust foundation for intelligent control and long-term process improvement.

IMPLEMENTATION PATH AND LESSONS LEARNED

Implementing EMG iCASS® in an industrial galvanizing environment is a structured process that blends technological readiness with organizational alignment. Successful deployment requires careful planning, robust data infrastructure, and close collaboration between line operators, automation engineers, and data specialists.

Prerequisites for Deployment

Before EMG iCASS® modules can be activated, several foundational elements must be in place. The availability of historical process and quality data—preferably covering a period of one year—is required to support robust model development and validation. In addition, real-time production data must be accessible through a stable interface to the PLC and relevant process instrumentation. Clearly defined quality specifications and production targets are also necessary, as they guide model training and the design of control logic. Finally, the system must include an appropriate infrastructure for executing machine learning models, typically a dedicated server or a virtual machine on-premise with remote access capabilities.

Step-by-step implementation process

The deployment of EMG iCASS® typically follows six stages. It starts with defining the application goal together with the customer, such as improving coating control or reducing safety margins. EMG then conducts an initial check of the historical data to ensure modelling is feasible. If the data quality is adequate, a proof of concept is developed and tested offline. After successful validation, the model is deployed into the EMG iCASS® system, linked to live data streams and connected with the line PLC. The system is then optimized during live operation, with control parameters and fallback mechanisms fine-tuned as needed. Finally, after thorough testing, the system is released for full production use, with continuous monitoring and optional retraining based on new data.

Lessons learned from industrial projects

Key insights from industrial EMG iCASS® projects highlight the importance of clean, consistent data, as poor signal quality delays model development. Effective collaboration between production, quality, automation, and IT teams helps resolve integration challenges early. Starting with monitoring and visualization before activating full control builds trust and allows refinement. Continued success also requires occasional model updates to reflect changing production conditions.

By following this approach, steel producers can successfully integrate EMG iCASS® into existing lines, enabling data-driven control strategies without overhauling legacy systems. The result is a scalable and sustainable digitalization pathway that brings measurable gains in efficiency, quality, and cost reduction.

CONCLUSION AND OUTLOOK

The EMG iCASS® platform represents a major advancement in intelligent process control. Exemplary shown here for the galvanizing process in steel production. By combining classical automation with real-time data analytics and machine learning, it enables a shift from reactive to predictive and prescriptive operations. The modular architecture allows users to address specific challenges such as strip transition control, safety margin optimization, nozzle alignment, and real-time coating regulation, all within a flexible, scalable framework.

Looking ahead, EMG plans to further expand the capabilities of iCASS® by integrating additional AI tools, extending compatibility to more process steps, and enhancing connectivity with higher-level systems such as

MES and ERP. Ongoing developments may also include self-adaptive model maintenance, automated anomaly detection, and tighter integration into digital twins.

With its proven foundation and forward-looking vision, EMG iCASS® provides a robust and future-ready solution for steel producers seeking to unlock the full value of their process data. The journey toward autonomous, data-driven production is well underway—and EMG iCASS® is a powerful enabler along that path.

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The Pathway to Autonomous Ironmaking

D. Bettinger, A. Fellner, H. Fritschek, K. Herzog, P. Krahwinkler, T. Kronberger, M. Schaler, C. Tauber, B. Voglmayr

Primetals Technologies Austria GmbH, Linz, Austria

Autonomous operation relies on automation and digitalization systems equipped with advanced control and learning capabilities. This paper examines key components involved in progressing toward autonomous ironmaking operation, with the goal of stable, efficient, and shift-independent processes.

Autonomous decision-making in ironmaking utilizes technologies such as artificial intelligence (AI) and machine learning (ML) to measure, control, and optimize process parameters.

Classical first-principles models, pure ML models, and hybrid models are compared in terms of their potential and limitations for automatic process control or the development of digital twins.

Various aspects of autonomous operation are reviewed, including sensor technology, condition monitoring, process optimization -, and production planning systems for ironmaking. Together, these elements establish the foundation for future autonomous ironmaking operations, enabling increasingly intelligent, adaptive, and resilient systems that minimize human intervention while maximizing efficiency and process stability.

KEYWORDS: AUTONOMOUS PLANT – PROCESS OPTIMIZATION – RULE BASED EXPERT SYSTEM – PROCESS CONTROL – CONDITION MONITORING – PROCESS SIMULATION

INTRODUCTION

This paper outlines steps toward an autonomous ironmaking plant operation, based on over 30 years of collaboration with voestalpine Stahl on ironmaking operational improvements. The work provides a comprehensive roadmap focusing primarily on proposing technologies and solutions that are already available in the most advanced plants. The aim of the autonomous operation is to achieve closed-loop control of the process, making it possible to sustainably run in automatic mode, leading to a shift-independent optimized operation.

Autonomous operation aims to minimize operator intervention across all areas where such an approach is deemed practical and effective. Figure 1 shows the benefits of autonomous operation in graphical form.

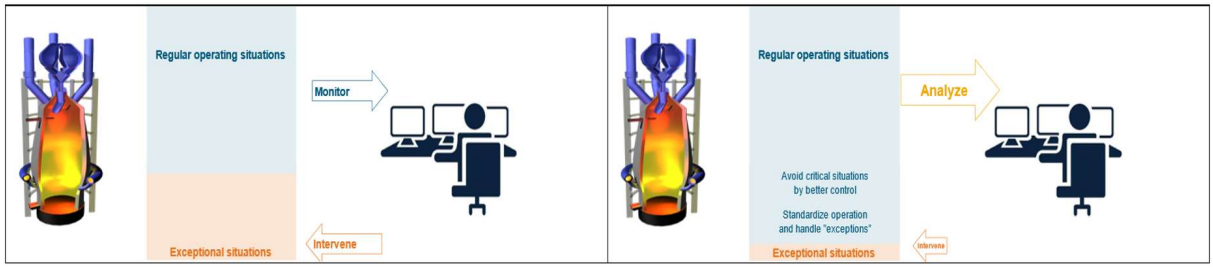

Fig. 1 – Conventional tasks of operation team and changed tasks with higher degree of autonomy

High data quality and reliable data supply are crucial preconditions for closed-loop and autonomous operation. This includes process data, raw material, as well as hot metal and slag-related data. Emphasis is placed on the integration of digital technologies to enhance the accuracy and timeliness of data collection. The roadmap excludes technologies that are still in development and those requiring extensive mechanical modifications, such as fully automated unmanned tapping. It also excludes unmanned maintenance.

The goal is to achieve a paperless, excel-free operation with no manual data entry. The steps described in this document are designed to be future-proof and provide a foundation for further developments towards the direction of fully autonomous operation.

OVERVIEW OF IMPROVEMENT STEPS

The roadmap to autonomous ironmaking operation involves a combination of automation, digitalization, and organizational measures. Implementing these changes requires a step-by-step approach and should be treated as a change management process. Involving all relevant stakeholders is crucial for defining a joint operational philosophy, which should be reflected in the optimization system's rule base.

Each stage involves evaluating current processes, identifying improvement areas, and strategically implementing technologies. Continuous monitoring and feedback are essential for sustained effectiveness.

- ***Assessment and Planning:*** Analyze operations to find improvement opportunities and set clear goals, schedules, and resources.
- ***Technology Selection and Integration:*** Choose and incorporate appropriate technologies such as automation, sensors, or data platforms.
- ***Implementation and Training:*** Deploy and test new systems; train staff to ensure effective adoption.
- ***Monitoring and Optimization:*** Track system performance and use data insights for ongoing process enhancement.
- ***Review and Continuous Improvement:*** Regularly assess impact and adjust for continuous advancement and alignment with new technologies.

ROADMAP TO AUTONOMOUS OPERATION

Autonomous plant operation is characterized by the ability to *control* a wide range of actions in the plant, and by *cognition* – the capability of the automation system to adapt and learn (see Figure 2).

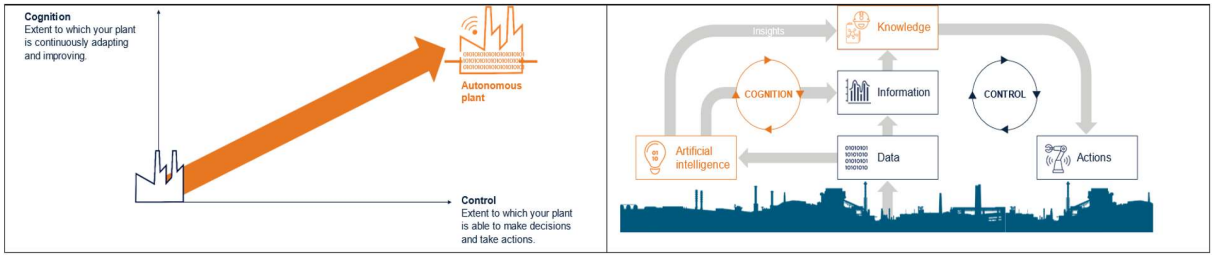

Fig. 2 – Pathway to autonomous operation: cognition and control "loop" of an autonomous system

The Digital Heart: Functions of a Modern Process Control System

Process control systems are the backbone of industrial automation, enabling precise, efficient, and safe operation. Contemporary control systems integrate hardware, software, and communication technologies to run industrial operations by providing the following core functions:

Process Monitoring: Real-time monitoring of process variables is a fundamental capability at the core of any control system. Sensors and transmitters collect measurement parameters which are continuously fed into the control system, providing a live overview of the process conditions.

Automatic Control: Using adequate control algorithms, the system automatically adjusts actuators like valves, pumps, and motors to maintain a stable and optimized process within predefined limits.

Data Acquisition and Handling: Various types of data storage systems are employed to support process control and enable historical data analysis.

Alarm and Event Management: To ensure safety and responsiveness, process control systems include alarm functions that notify operators of abnormal or hazardous conditions. These alarms are prioritized and logged, enabling timely intervention and root cause analysis.

Advanced Control: Beyond basic control, advanced process control (APC) techniques such as model predictive control (MPC) are employed to optimize operations. These methods enhance throughput, reduce variability, and minimize energy consumption.

Safety and Interlocks: Safety Instrumented Systems (SIS) are integrated into the control architecture to handle emergency shutdowns and prevent unsafe conditions. Interlocks ensure that operations proceed only when all safety criteria are met, protecting both personnel and equipment.

Human-Machine Interface (HMI): Operators interact with the system through intuitive graphical interfaces that display process flows, alarms, and performance metrics. HMIs facilitate manual control, diagnostics, and decision-making, bridging the gap between human oversight and automated control.

System Integration and Communication: Modern control systems are designed to integrate seamlessly with process optimization systems, condition monitoring systems, and enterprise-level platforms such as Manufacturing Execution Systems (MES) and Enterprise Resource Planning (ERP) systems.

In summary, modern process control systems are multifaceted platforms that combine real-time control, data intelligence, and system integration to drive operational excellence. Their evolution continues to be shaped by advances in digital technologies and cybersecurity as well as from experienced operators.

CREATION OF A DIGITAL IMAGE

Online transmission of measurements and high data quality are important for automatic operation. It is necessary to ensure that all data are received consistently, accurately, and on time. Many plants monitor process parameters continuously but do not have access to real-time data regarding the chemical and physical properties of input and output materials. Currently, this information is usually obtained only a few times per shift and may be delayed by several hours due to sampling and laboratory analysis processes.

For instance, following nonstandard measuring devices and soft sensors contribute to a more stable and automatic operation of a blast furnace:

Online Tapping Temperature: The use of dual-wavelength pyrometers enables early response and accurate prediction of thermal conditions, thereby ensuring an optimized and controlled tapping process. Over time, this contributes to a reduction in the consumption of reducing agents.

Material Type Indication: Automated systems identify the type of material being used to avoid charging the wrong material, which can lead to inefficiencies and potential damages.

Automatic Indication of Tapping Start and End: Accurate tapping signals enable precise calculations of liquid levels, thereby supporting optimal operation of the blast furnace.

Online Grain-Size Measurement: Most plants lack continuous physical raw material data. Online measurement ensures real-time access to this critical information for efficient and undisturbed operation.

The integration of such sensors makes the creation of a digital image of ironmaking operations possible and allows for real-time monitoring and control. Additionally, the implementation of redundant systems and backup sensors ensures continuous data availability, even in the event of sensor failure - thereby preventing unplanned downtime.

DATA QUALITY, DISTRIBUTION, AND STORAGE

Ensuring high quality data involves the use of advanced data validation techniques to filter out any erroneous values and regular maintenance and calibration of sensors. Numerous data validation techniques are employed, such as redundant measurement comparison, limit checks, balancing methods, KPI monitoring, and advanced trend and pattern recognition strategies.

The subsequent step involves distributing the data across multiple systems using state-of-the-art methodologies, adhering to the single source principle and ensuring data integrity without loss. It is crucial to select appropriate data distribution mechanisms - such as **Data Brokers and Middleware** - to facilitate

secure, scalable, and real-time data exchange across various layers and systems, supporting both vertical and horizontal Integration.

Structured Data Storage: Efficient conversion of data to information is facilitated by keeping data in a suitable format and structure - ready for usage for the dedicated application. ***Data Warehouses*** with dedicated data marts are usually the most efficient solution to provide data in a suitable format, optimizing the access for data analytical evaluations as well as for Business Intelligence applications

Furthermore, dedicated structures can be essential for analyzing specific data sets. For instance, for the ***Matrix Mining*** application, blast furnace charging and performance data are stored in a smart way, enabling efficient analysis of charging patterns with respect to plant efficiency and performance.

An additional method is extracting relevant characteristic parameters out of extensive data sets (e.g. image data as 2D temperature data from the shell of the blast furnace or the acoustic top temperature measurements or the shape of the burden surface in the blast furnace) to allow for further analysis and usage in control functions.

While data duplication (as in different data marts) can be a wanted feature, smart data handling avoids duplication of data in different systems but aims at a single-source principle using central data hubs and data storage systems that can be accessed by different automation systems from different levels.

FROM DATA TO INFORMATION

Sufficient *data* to create a digital image of a plant is the required basis, but extraction of the *information* carried by the data is relevant for the operation of a plant. There are multiple ways to extract information from data such as various types of statistical models and data analysis methods.

Models and Digital Twins

In simple systems, intuitive interpretation of a limited number of data points is sufficient to extract relevant information. However, in state-of-the-art ironmaking plants, the sheer volume of sensor inputs and data - along with their complex interrelationships - exceeds human interpretative capacity. Various types of models are therefore employed to convert raw data into information: these include empirical and first-principles models, condition monitoring models (for both equipment and processes), data-driven models utilizing machine learning (ML) algorithms, hybrid models that integrate first-principles with ML approaches, and advanced models leveraging performance-intensive algorithms such as discrete element methods (DEM) and computational fluid dynamics (CFD).

Models serve several distinct purposes, including process optimization, predictive maintenance, and emergency response. When a model accurately reflects the characteristics of a real-world system, it is commonly referred to as a ***Digital Twin***. Multiple digital twins exist, each representing different aspects of an industrial facility. For autonomous ironmaking, a holistic digital twin of the process would be of special interest, as they provide the ability to perform simulations that could be used to test different scenarios and identify the most efficient operating conditions

The creation of holistic digital twins of ironmaking processes involves the integration of various data sources, including sensor data, material data, and product data. Holistic digital twins are already available for some processes, such as sintering and pelletizing. In contrast, processes like the blast furnace require sophisticated modeling techniques - such as DEM and CFD - to produce an accurate and detailed representation. Machine learning algorithms can further accelerate the computation time of such resource-intensive models. Given the inherent complexity of the blast furnace process, a fully comprehensive digital twin remains a future challenge.

Data Analytics, Machine Learning, and Business Intelligence

Data analytics (DA), artificial intelligence (AI), including ML, and business intelligence (BI) are essential tools to gain new insights into process conditions.

Business Intelligence provides analysis of production data, identifies trends, and supports informed decision-making.

Artificial Intelligence applies data analysis methods, such as ML and advanced statistics to find new metallurgical patterns even in high dimensional and complex data sets.

Implementing comprehensive data analytics, AI, and BI strategy involves establishing a centralized data warehouse to store and manage all production data. This data warehouse provides the foundation for advanced data analysis and decision-making. Enhancing the data warehouse with a database add-on that supports big data analytics enables the analysis of large and complex datasets.

Hybrid Models and Transparency Approach - Light into the Black Box of AI Models

First-principles models, grounded in physics and chemistry, simulate core aspects of plant operation. The model assumptions usually provide a clear validity range. However, for complex, nonlinear systems with a high number of input parameters it is difficult to build such models.

AI and ML techniques can be used to find metallurgical patterns within the data to develop predictive models. The most reliable guidance comes from hybrid models that blend first-principles physics with AI and ML techniques. This hybrid approach marries the rigor of physical laws with the pattern-finding power of ML, yielding models that are performant, accurate, and transparent.

For further increasing the transparency, evaluation engines perform meta-analyses to clarify whether results come from established experience or from extrapolation into unknown territory. A meta-analysis assesses reliability, sensitivity to changing inputs, differences between AI/ML, and conventional models to indicate model reliability and provide confidence funnels to gauge trustworthiness.

Explainable AI methods help distinguish true causal relationships and coincidental learning from mere correlations, preventing misleading conclusions which is essential when the results are used in the decision-making chain of a critical process as in ironmaking.

PROCESS OPTIMIZATION: DECISION-MAKING BY CLOSED-LOOP EXPERT SYSTEMS

The Plant Expert System monitors and forecasts the process status, provides alarms for disturbances, and suggests control measures and corrective actions. It is implemented as a rule-based decision system.

For instance, in case of a blast furnace this includes all relevant plant areas from the material selection to charging, the blast and fuel injection until the tapping - both for regular operation as well as for start-up and shut-down procedures.

The closed-loop expert systems use advanced algorithms and ML techniques to continuously optimize ironmaking operations, ensuring that the system can adapt to changing conditions in real-time and make informed decisions based on valid data. These systems provide operators with real-time information and guidance, allowing them to make proactive adjustments to optimize performance and to address potential issues before they become critical.

Implementing closed-loop expert systems involves developing a comprehensive control strategy that includes setpoints, control loops, and optimization routines. This strategy should be continuously reviewed and updated based on data analysis and feedback from the system as well as from experienced operators.

CONDITION MONITORING AND PREDICTIVE MAINTENANCE

A learning condition monitoring system assesses the equipment status and provides guidance for predictive maintenance. This system complements the expert system for regular operations and assists in emergency situations. The following components are included:

Condition Monitoring Sensors: Continuous monitoring of furnace equipment using sensors enables early detection of potential issues before they become critical. It continuously analyzes data from various sensors to evaluate the condition of key equipment, detecting patterns and trends that may signal emerging issues.

Predictive Maintenance Algorithms: Implementing algorithms that use data from *Condition Monitoring Sensors* to predict when maintenance is needed. Predictive maintenance involves the use of algorithms and ML techniques to predict when maintenance is needed.

Maintenance Planning and Execution: Developing a maintenance plan based on *Predictive Maintenance Algorithms* to ensure that maintenance is carried out proactively and efficiently. This plan includes schedules for regular maintenance, as well as procedures for addressing potential issues identified by the condition monitoring system.

A modern and proactive condition monitoring system reduces downtimes, extends the life of plant equipment, and improves overall reliability.

PRODUCTION MANAGEMENT AND ORGANIZATIONAL INTEGRATION

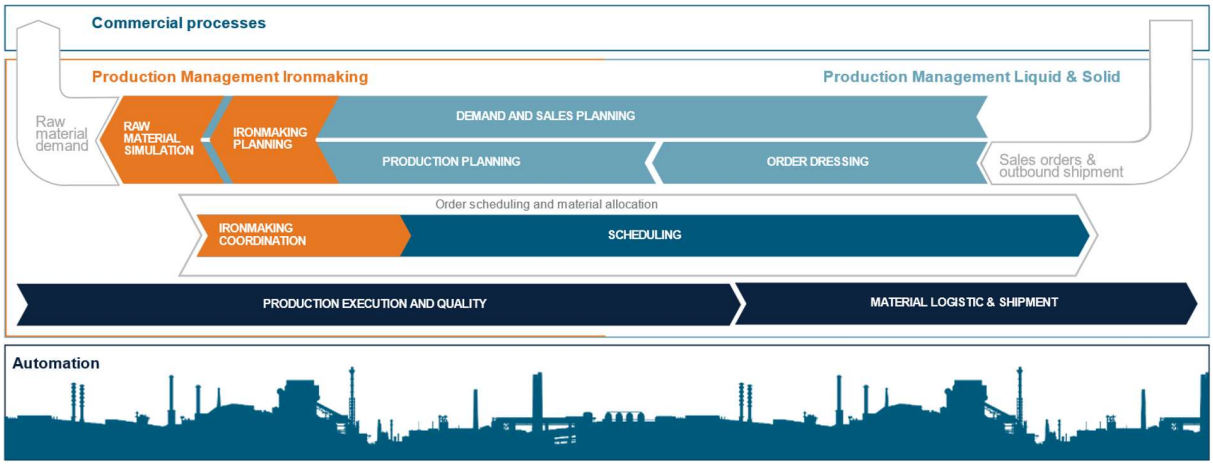

Fig. 3 3– Production management ironmaking

The Production Management System for the ironmaking area optimizes planning and coordination of ironmaking plants. The following components are included:

Raw Material Simulation: Raw material simulation considers conversion cost to optimize raw material selection. It uses data from various sources in combination with advanced modeling techniques to forecast the use of raw materials in furnace operations.

Long-Term Production Planning: The system develops a long-term production plan that considers the availability of raw materials, equipment status, and market demands.

Short- and Medium-Term Plant Coordination: Coordinating the activities of the ironmaking plants in the short and medium term ensures that they operate efficiently and at target productivity.

The production management system integrates with the process control and optimization systems to provide a comprehensive view of plant operations, enabling informed decision-making and maximum coordination (see Figure 3). This system enhances the planning and coordination of ironmaking plants, thereby improving overall efficiency and productivity.

VIRTUAL PLANT SIMULATION - TEST AND TRAINING

With a high degree of automation, operators rarely need to make decisions. However, if the system fails, they must quickly take control - often in critical situations that reflect rare and unfamiliar operational situations. To maintain their decision-making skills, regular training simulations are recommended.

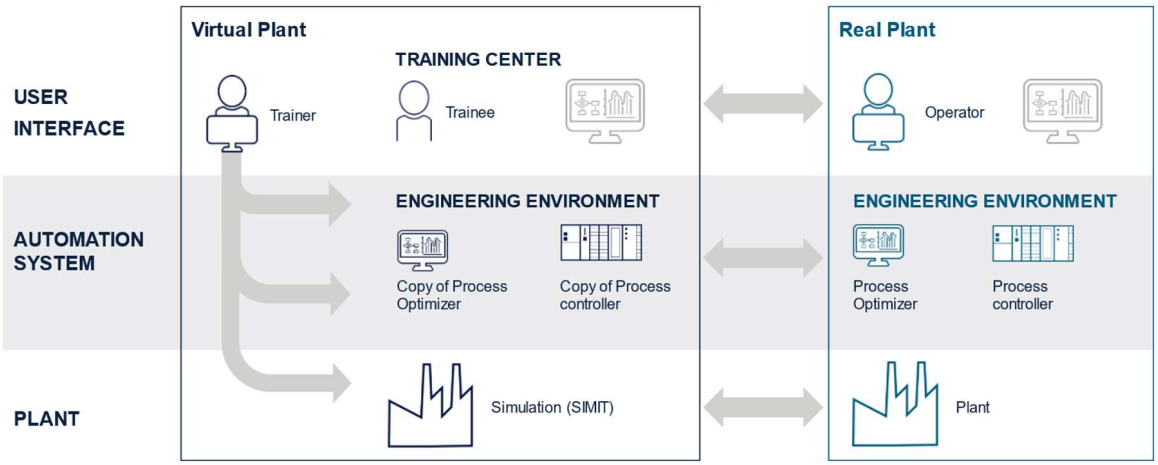

Fig. 4 4– Virtual plant for testing and training

The operators benefit from a realistic, risk-free training environment, enabling learning by doing. Further, a Virtual Plant provides the possibility to test software modifications before actual installation in the productive system. This way, risks of any critical flaws are minimized.

A Virtual Plant replicates both the process control system and the process optimization system of the real plant, but substitutes real plant data with simulated field responses, including the ability to simulate equipment malfunctions and observe system responses (see Figure 4).

LIMITATIONS OF AUTONOMOUS OPERATION

While the roadmap provides a comprehensive guide towards autonomous operation, there are several limitations to consider:

Fully autonomous operation must cover all potential operational conditions, from normal and emergency operations to startup and shutdown, equipment failures, and instrumentation issues. Hence, the challenges for autonomous operation increase with the complexity of the plant.

For instance, for a blast furnace operational conditions as scaffold formation and removal, slipping and hanging, center and wall operation, pressure build up, dead man behavior, tapping problems, and many others must be considered. This is important as wrong operational decisions can lead to huge problems or even to disasters within a short time. While full autonomy is not yet feasible for iron-making plants, limited autonomous control under standard conditions is possible and offers the benefit of standardized and optimized operation.

However, it may be advisable to exclude certain tasks from automation for various reasons such as:

Cost Considerations: In areas like the blast furnace cast house, high-cost and maintenance-heavy robots are not feasible, especially since they can’t yet match skilled operators in unexpected or emergency situations.

Technological Maturity: Key technologies required for achieving full autonomy - such as advanced predictive analytics and comprehensive metallurgical digital twins of ironmaking plants - are still under development and may not yet offer full reliability.

Integration Challenges: Integrating new technologies can be complex and costly as it may require significant modifications to the current infrastructure.

Data Quality: Reliable autonomy depends on high-quality, consistent data, which in turn requires rigorous data management and sensor maintenance.

Human Factors: Human oversight remains essential, with proper training and change management needed to address resistance and ensure effective use.

Regulatory and Safety: Meeting regulatory and safety standards for autonomous systems requires careful validation and ongoing compliance.

SUCCESS FACTORS

Successful implementation of autonomous blast furnace operations depends on the following key factors:

Management Commitment: Strong leadership and commitment from management are essential to drive the transition to autonomous operations. This includes providing the necessary resources, setting clear goals, and supporting the change process.

Stakeholder Engagement: Involving all relevant stakeholders, including operators, process and automation engineers, maintenance personnel, and IT staff, is crucial.

Continuous Improvement: The journey towards autonomy is an ongoing process, requiring continuous monitoring, evaluation, and implementing a culture of continuous improvement.

Training and Development: Providing comprehensive training programs for the workforce ensures that they have the necessary skills and knowledge to operate and maintain the autonomous systems.

Robust Data Management: Ensuring high data quality and reliability is critical for autonomous operations. This involves implementing robust data management practices, regular maintenance of sensors and instrumentation, and continuous validation of data as well as the underlying validation rules.

Advanced Technologies: Leveraging advanced technologies, such as AI, ML, and advanced models closely interacting with closed-loop Expert Systems is essential for achieving autonomy.

INSTALLATIONS

Expert Systems are a key element for autonomous operation. Over 100 Closed-Loop-Expert Systems have been installed in sinter, pelletizing, direct reduction, Corex, and blast furnace plants, leading to standardized processes and cost savings. Several plants have already successfully implemented the full integration of all systems, including advanced cognitive elements that facilitate learning of automation systems, thus establishing the foundation for autonomous operation.

CONCLUSION

The roadmap to autonomous ironmaking plant operation involves a combination of automation, digitalization, and organizational measures. By following the outlined steps and addressing the listed limitations, it is possible to achieve a closed-loop operation that is sustainable and efficient. High data quality, reliable data supply, and continuous stakeholder engagement are crucial for success. The proposed steps are future-proof and provide a foundation for further developments towards fully autonomous operations.

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DYNREACT – AN OPEN-SOURCE PRODUCTION PLANNING SOFTWARE

C. Nölle[1], J. Brandenburger[1], A. Wolff[1],
E. Sirovnik[2], C. Schirm[2], D. Müller[2],
M. Gutiérrez[3], J. Ordieres-Meré[3],
M. Vanucci[4], V. Colla[4], L. Laid[4]

[1]VDEh-Betriebsforschungsinstitut, Düsseldorf, Germany
[2]Thyssenkrupp Rasselstein GmbH, Andernach, Germany
[3]Escuela Técnica Superior de Ingenieros Industriales, Universidad Politécnica de Madrid, Spain
[4]Scuola Universitaria Superiore Sant'Anna, Pisa, Italy

We present the open-source planning software DynReAct, which grew out of a research project on dynamic production planning and scheduling in the steel industry. The software implements a three-stage approach to the flexible flow-shop planning problem, comprising modules for long-term, mid-term and short-term planning. The DynReAct software comes with a set of configuration options and pluggable interfaces that enable adaptations to different use cases. A flat steel sample use case is included in the open-source package and will be used to showcase the features of the software and the interaction between the different planning levels. The main concept of the implementation publicly available is to see it as a team of components with specialized roles, each contributing to the overall goal of dynamic reaction and proactive decision-making in production planning.

KEYWORDS: PRODUCTION PLANNING – SCHEDULING – OPEN SOURCE – FLAT STEEL – OPTIMIZATION

A modular framework for production planning

The hierarchical planning components are designed in a modular way, which allows for a gradual adoption of the platform or even the deployment of individual components only. The long-term planning is an order-less continuous flow model, responsible for strategic planning on the timescale of weeks or months, whereas the mid-term planning creates production schedules based on order backlog, plant availability and long-term targets. The integration of real-time plant status information is realized in terms of so-called plant performance models, which in combination with the short-term planning module enable the consideration of plant breakdowns and other unforeseen events. The necessary adaptation of the components to specific production plants requires the provisioning of a plugin module that encapsulates site-specific constraints and objectives.

The open-source software includes the following components:

- **Long-term planning**: the strategic planning component included is a placeholder, which needs to be replaced for actual productive use.
- **Mid-term planning**: this component generates the production schedules, which is an NP-hard optimization problem in general [1]. It is realized in terms of a tabu search optimization in combination with a travelling salesman solver, similarly to the approach described in ref. [2].
- **Short-term planning**: this is the component that addresses immediate operational challenges. It responds to disruptions, optimizes resource allocation, and adjusts the plan in real time for smooth execution. It can be conceptualized as a quick-thinking floor manager who makes on-the-spot decisions to keep production. The optimization is realized in terms of an agent-based auctioning system.
- **Sample use-case**: a plugin adapted to a fictional flat steel col-rolling mill, defining the objectives for the mid-term and short-term planning modules.
- **User interface**: A web-based user interface is included, which allows the user to trigger the different planning components and visualize the results.
- **REST service and API**: integration of the software into third-party applications can be realized via its

REST service and the implementation of specific coupling interfaces.
The software is available on Github [3].

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