Systematic Application of AI to Quality Optimization From Steelmaking to Galvanizing

Digital technologies are transforming industry at all levels. Steel has the opportunity to lead all heavy industries as an early adopter of specific digital technologies to improve our sustainability and competitiveness. This column is part of AIST's strategy to become the epicenter for steel's digital transformation, by providing a variety of platforms to showcase and disseminate Industry 4.0 knowledge specific for steel manufacturing, from big-picture concepts to specific processes.

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Since cost and quality optimization of individual processing steps in the manufacturing cycle of long and flat steel products has been an ongoing effort for decades, non-disruptive approaches for further optimizations are about to reach their technical limits. While applications of artificial intelligence (AI) and machine learning (ML) pushed the boundaries of those optimizations, their usually punctual application to individual steps of the steelmaking process significantly hampers their potential. Even with these relatively new technologies, new ideas are required to reach new grounds in quality and cost improvements.

During the history of steelmaking, many cross-process optimizations were developed based on human expertise that was gathered over the decades. These optimizations are so omnipresent that they are easily overlooked, e.g., alloying configurations govern the mechanical properties of the end product but also have great influence on defect rates during both casting and rolling. Another example is that slabs are often sorted out after casting if it is expected (by experience) that the slab may have problematic inclusions that could lead to defects in the rolled or finished product. Various quality control systems constantly assess produced material and decide — often via manual inspection by humans — if the material is suitable for the next processing step.

This aggregated knowledge of expert steelmakers is what leads to the high-end but still affordable steel products that are available today. To fully unlock the potential of artificial intelligence in steel manufacturing, the AI approach must be lifted from punctual applications to the holistic level that is currently only taken by the human steel experts. In fact, punctual application of AI to individual processing steps could even counteract valuable achievements in an upstream or downstream process due to imposed requirements on input material or a single objective cost optimization at the expense of output quality.

Besides its major benefits in quality improvements and cost reduction, a systematic and integrated approach to artificial intelligence also enables other applications:

- Addressing the need of transparent CO_2 and energy efficiency tracking of steel producers. Transparent tracking of material in combination with machine learning allows for the assignment of accurate CO_2 footprints to individual material pieces and their processing steps. This can serve both as a selling point for the steelmaker as well as for identifying how to tune all production routes for CO_2 energy efficiency. This is of particular importance during the transformation process from conventional blast furnace–based production to direct reduced iron (DRI)-based production.
- Predictive maintenance applications could be lifted from an individual process to a holistic level in parallel.
- Productivity and cost efficiency of the production site will improve significantly.

Establishing such an end-to-end optimization requires a systematic approach regarding data handling, quality monitoring and plant integration. Also, the transition needs to take place in parallel with the existing steel manufacturing systems and must not interfere with ongoing steel production. These and some other requirements addressed in the next section make such a transition challenging.

The article is structured as follows: First, the requirements of a fully integrated steel process optimization are described, starting with the finished end product (e.g., flat or long) going up the value chain from finishing to cold rolling to pickling to hot rolling to continuous casting to the meltshop.

Then, in a second loop through the value chain, problems and solutions addressing the requirements together with AI-based solutions for the relevant stages are presented. The feasibility of a fast approach to such a project has been demonstrated in collaboration of Smart Steel Technologies GmbH (SST) with ArcelorMittal Eisenhüttenstadt[1] and ArcelorMittal Duisburg,[2] which will serve as example projects in the last sections of this article. First, a surface defect reduction on ultralow-carbon (ULC) interstitial-free (IF) flat products for automotive exposed material that was achieved via optimized casting parameters is discussed. Then, starting from the casting machine, the second example continues through secondary and primary metallurgy, covering all processes of steelmaking and liquid steel treatment. Both examples demonstrate that a fast adoption of the presented technologies does not interfere with the daily operation of production.

Requirements for Holistic Process Optimization

What makes up a holistic or vertically integrated optimization approach? It means that any optimization takes both direct and indirect upstream and downstream processes into account. For example, an optimization during casting should not only aim for lower slab downgrading, but also for a reduction of casting-related defects that only become apparent in the following hot or cold rolling and galvanizing steps. At the same time, optimized heats ordered from the meltshop must respect meltshop and casting constraints (such as casting speed or superheat constraints) and should consider heating cost and alloying configuration.

Implementing such an integrated and systematic approach in any steel mill is a very challenging project and requires tight collaboration of metallurgy, steelmaking, data science, machine learning and IT experts. This cross-disciplinary expertise allows tackling key success requirements of such a project. The first fundamental one is a reliable and automatic detection, labeling, rating and quantification of quality deviations. The correct labeling and detection of defects is a necessity to compose training data for quality prediction models. The standardized rating (such as severeness) and quantification (e.g., defect area or deviation from target value) is required as a target signal for various ML and optimization models and is essential for measuring project success in the form of achieved defect reduction. These processes and their data handling should be standardized for different steel grades, time intervals, production settings and across all production processes.

The other fundamental requirement is the consolidation of multiple data sources distributed over the plant and mapping between material pieces. To include the meltshop and continuous casting process in the optimizations, defects on a coil, billet, tube or other product must be mapped to their respective position on preceding milling stations up to their position on the strand. This allows for the defect to be related with the individual casting parameters that were used to cast this piece of strand (e.g., casting speed, cooling configuration) and information about the used heat (e.g., superheat temperature, chemical composition, degassing parameters). Here the integration of different level 1, level 2 and level 3 systems becomes relevant, as the processing parameters of the various processing steps must be tracked for each piece of produced material.

Built on this foundation, it is possible to create ML models for a current (upstream) process that compute the optimal process settings and optimal process operation in on-line, live mode to minimize process and quality deviations. The key is to avoid process and quality deviations before they occur. The same models are able to predict quality, but actively avoiding deviations is the main driver to improve manufacturing processes. This applies to all processes of steel manufacturing.

Winning the Fight Against Slivers: ArcelorMittal Eisenhüttenstadt

This section presents specific results for automotive exposed IF (ULC) steel grades that demand the highest standards of surface quality. The high quality requirements on automotive exposed ULC steel and the known casting behavior of these grades render these materials specifically susceptible to surface quality defects such as slivers.[3–8] Those defects often only become apparent after cold rolling and galvanizing, which makes them costly. With the approach described here, sliver rates at ArcelorMittal Eisenhüttenstadt were reduced by more than 50%.[1]

To achieve quick results, it makes sense to prioritize steel grades or end products that promise the largest optimization potential. This reduces the initial complexity to integrate with and analyze the data of the various different systems in a plant. For example, to improve the surface quality of automotive exposed steel, it suffices to fix surface inspection at the galvanizing line to obtain a valid target signal for optimization and then use that to optimize the casting process. This prioritization leads to fast results with direct and substantial economic effect. A following extension of the integration and optimization to the remaining production lines and steel grades is then eased by the experience gathered during the first project phase.

Reliable Defect Classification — Flat steelmakers usually have installed automated surface inspection systems (ASIS) at the end of the hot strip mills, continuous pickling lines and continuous galvanizing lines. These systems take images of the top and bottom of the strip as it passes by. Whenever there is an irregularity in the texture of the steel surface, an image of that part of the strip is passed to an image classifier. The purpose of the classifier is to automatically determine if the irregularity is not relevant at all (so-called pseudo-defects, water droplets, irrelevant shadows, etc.), or if the image contains a relevant defect; that is, scratches, scale defects, slivers, ungalvanized spots and more.

Currently, none of the existing ASIS provide defect classification robust and accurate enough to be used in automated process optimization. For example, all ASIS have problems distinguishing complex defect types such as slivers from completely different defect types like scratches. The reason for this is outdated classification algorithms. Therefore, state-of-the-art, image classification based on deep learning should be applied instead. Best results have been achieved with deep convolutional neural network (CNN) classifiers specifically designed for steel surface images taken at individual steel processing steps.

Deep CNNs that were specifically designed by Smart Steel Technologies for defect classification on the different types of steel processing lines form the core of the surface inspection component. These network topologies are then fine-tuned with plant-specific training data and beat any other method in terms of labeling accuracy.[9]

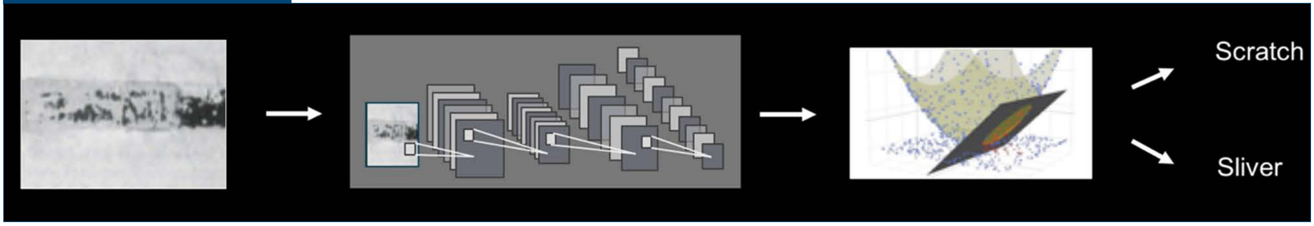
Deploying the deep CNN-based defect classifiers on-site in the plant's data center and using a graphics processing unit (GPU) accelerated inference ensures high throughput and low latency of the classification results, enabling live classification of defects where the delay is governed by the image data feed from the cameras and their associated software. As a side effect, defect image classification is standardized for the whole production site, regardless of the supplier of the camera hardware.

An extra level of labeling quality, i.e., even lower false positive and false negative rates, is achieved by cross-referencing potential defects to preceding manufacturing steps. This becomes possible by the uninterrupted tracking of material within the plant described in the following sections.

Cross-Process Data Transformation and Centralized Coil Maps — Using fully automated, position-based data matching, all defects and classification results from hot rolling, pickling and galvanizing are mapped into a joint coordinate system creating a precise digital twin of each slab/coil as it propagates through the plant. This transformation tracks any kind of manipulation performed on the material, including uncoiling, upcoiling, flipping, cutting, seam welding, cropping and trimming — even including inspection lines.

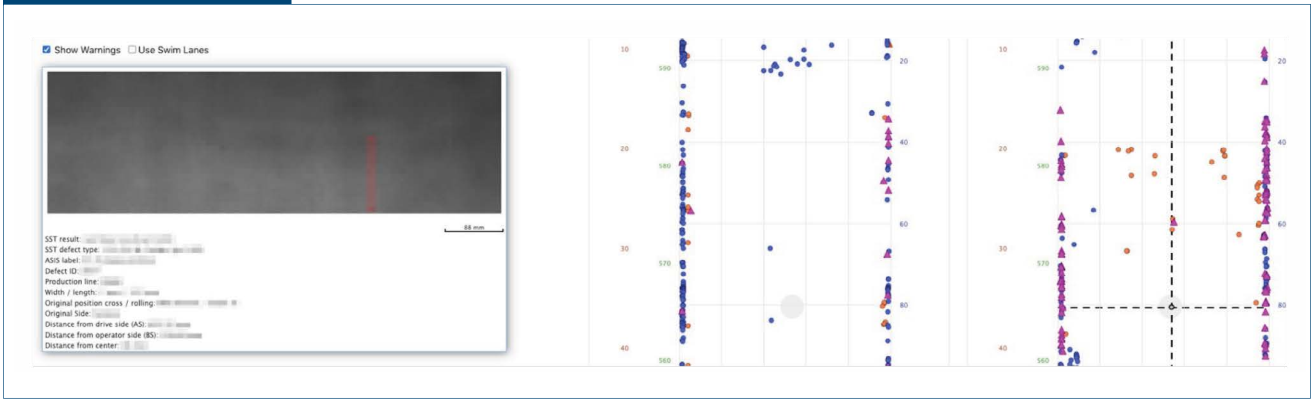
This becomes possible with the accurate integration of the plant's level 2 and level 3 systems from which respective rotations, flips, crops, welds, etc., are replicated during manufacturing. On top, the accuracy and robustness of position-based data matching is improved by ML models that are able to detect matching errors automatically and — on the other hand — automatically cluster surface defect images from hot rolling, pickling, galvanizing that show the same defect at the same position of the strip. The resulting consolidated information can be examined using a modern, browser-based user interface (UI, Fig. 2). Here the production path of material as well as all classified defects, including the corresponding images and metadata, are displayed, allowing for quick quality improvements or degradation over individual processing steps. Corresponding defect reports can be generated automatically and directly downloaded for each coil as a PDF.

Figure 1



Deep convolutional networks translate images into a linearly separable space for classification.

Figure 2



Centralized coil map: defect classes (colors) from different mills (symbols) and sheet sides (top and bottom in individual axes) are mapped into a joint coordinate system. Individual defect images (left) can be displayed by simply hovering the markers.

To facilitate day-to-day work with surface images, distribution of casting parameters and exploration of historic defect rates, Smart Steel Technologies installs additional web-based applications in the plant's data center that can be accessed by authorized personnel from within the plant. These tools include a defect image search based on deep learning methods, a training set optimizer, and a training set projector and have been proven valuable since their first appearance in 2019.

Transparent Insight Into Quality-Relevant Process Conditions — With all defects mapped to their position on the cast strand, what remains is to automatically relate casting and meltshop data to the defects — this is done with so-called process analyzer tools. These tools aggregate defect data from hot rolling, pickling, galvanizing, and level 1, level 2 and level 3 data of the meltshop and continuous casting machine to strand segments (e.g., 50 cm), thereby building the necessary process context that relates achieved (surface) quality to (casting and meltshop) process parameters.

Clearly, the casting process of a particular 50 cm piece p1 of strand at time t1 may be influenced by events that happened earlier, at time t0, while the preceding piece p0 had been cast. Note that dependencies also exist in the opposite direction. Casting conditions of p1 can influence achieved quality results of p0. To complicate things even more, typical ladle sizes of 250 metric tons and the very purpose of continuous casting widen the required time window of analysis further. Full casting sequences, including the corresponding meltshop campaign, have to be considered to describe the casting context of each slab.

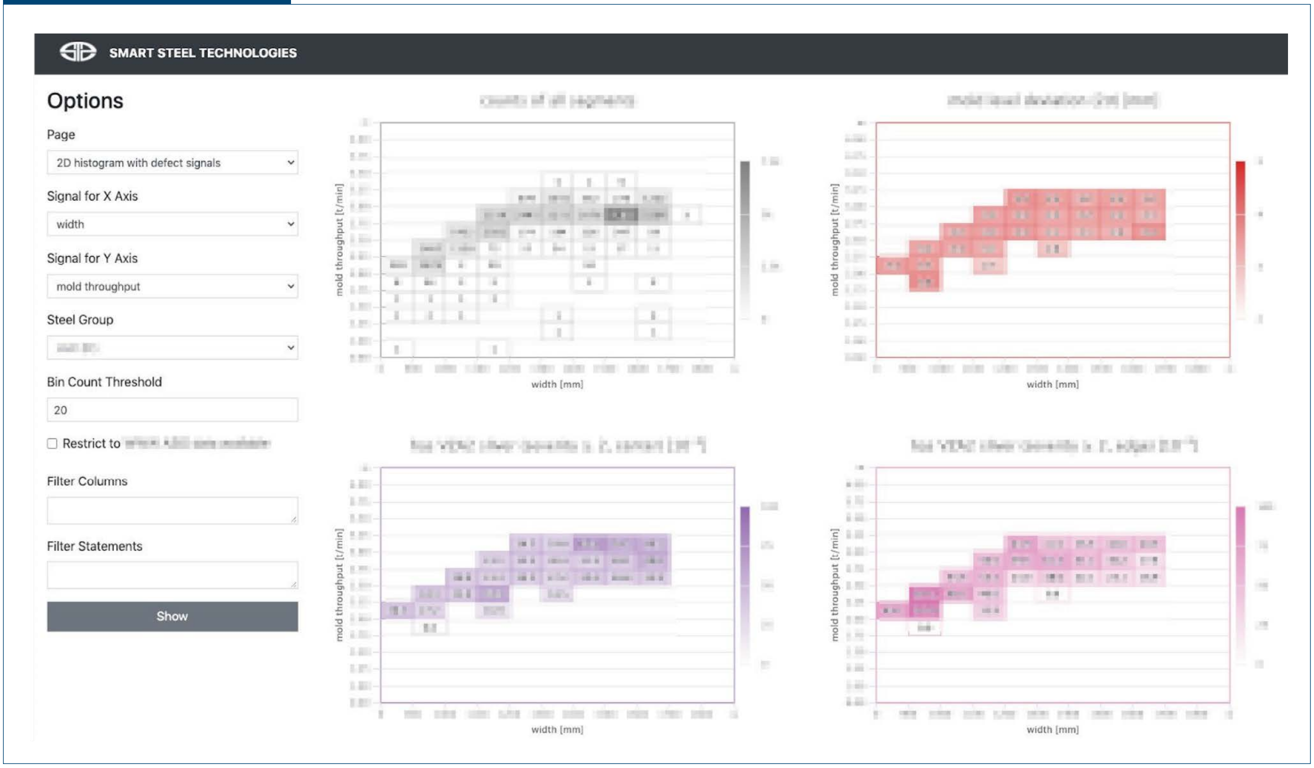
Process analyzer tools allow for two-parameter combinations of casting and/or meltshop parameters and their influence on achieved quality of particular steel grades or selected sets of cast slabs. In ML terminology, the process analyzer allows the feature space of the caster. For many non-trivial root-cause analyses, this tool alone allows engineers to find solutions in days compared to years (Fig. 3).

Automated Computation of Optimal Casting Parameters — The segment data displayed in the process analyzer also serves as a training set for surface quality models that are an integral part of the automated AI-based casting optimization. These models are based on Gaussian processes where recent algorithmic advances allow efficient multi-GPU acceleration and enable applications on large-scale data sets[10,11] — the magnitude of available categorical and continuous meltshop, casting and rolling parameters became computationally tractable with this kind of algorithm. The input of such a model is a set of casting parameters (e.g., casting speed, submerged-entry nozzle (SEN) submersion level, mold width) and heat parameters (e.g., superheat temperature and chemical composition) from which a probabilistic measure of the expected surface quality (e.g., expected rate of slivers) for a specific downstream line (e.g., galvanizing) is computed.

Based on these models, optimal values for continuous and discrete casting and meltshop parameters are searched, i.e., which parameters result in the best quality (e.g., minimization of slivers). Here, the challenge lies in high dimensionality of the parameter space (numerous meltshop and casting parameters have to be considered within one multi-variate model) and in the highly complex constraints that are put on the optimization. These constraints originate from both business requirements and physical limits of the casting equipment and often introduce dependencies between multiple casting parameters that are subject to optimization.

Via a direct integration into the casting planning system, the optimization goes far beyond the computation of optimal parameters per slab. Indeed, the AI-based model reorders slabs within the casting

Figure 3



Interactive exploration of the feature space of a caster. The process analyzer provides historical surface quality (derived from surface inspection at hot rolling, pickling, galvanizing) as a function of various casting and meltshop parameters.

sequence to minimize quality deviations and downgrading/reallocation. The system produces individualized optimal settings for all slabs within a sequence, as well as for each individual heat and for the full sequence. These are written back into the plant's level 2 system in a fully automated way.

Additionally, the caster operators are supported through live AI models that recompute the optimal settings continuously, taking into account changes that occur during the running sequence. This allows for recommendations to be made in on-line mode, such that operators can react in an optimal manner to each potential deviation from the original casting plan.

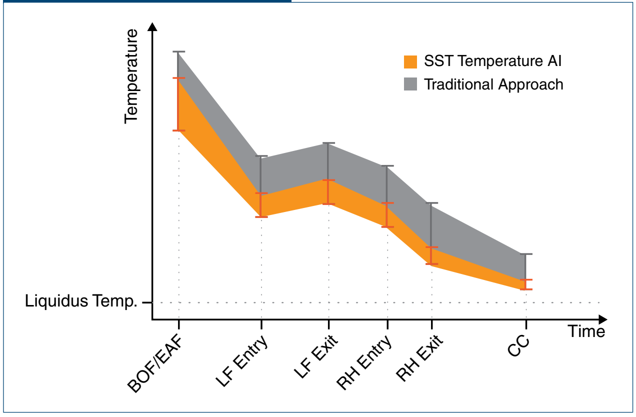
The operator at the casting machine then orders heats from the meltshop matching the proposed optimal configuration and cast accordingly. The next section explains how the heat specifications for a heat arriving at the caster can be met precisely.

Targeting Tundish Temperatures

While the preceding section includes temperature modeling and optimization, its focus lies on the casting optimization to reduce casting-related defects in the finished flat product. In this section, the focus shifts to cost reduction via advanced temperature control. This as well poses a cross-process optimization, as it covers the full range of primary and secondary metallurgy treatments. In addition to others, this model is running in the basic oxygen furnace (BOF) meltshop at ArcelorMittal Duisburg, Germany,[2] and in the electric arc furnace (EAF) meltshop of Marienhütte in Graz, Austria. The approach is suitable for large, complex meltshops, but is also profitable for smaller plants. The case of ArcelorMittal Duisburg also shows that AI-based temperature control is perfectly suitable for handling the vast quantity of different steel grades and the corresponding variety of heat treatment protocols that are in place at advanced meltshops of high-quality long products steelmakers. Again, quick wins can be achieved by focusing on the steel grades that are produced frequently and tend to have the highest temperature variance or temperature buffers and hence promise the highest benefit.

One of the most important parameters throughout secondary metallurgy is the temperature of the liquid steel at the different processing stations. Depending on the steel grade and treatment protocol, the tapping temperature can be lowered by up to 10 K and still arrive at the caster with a sufficient buffer above the liquidus temperature, and thereby save energy and cost. This becomes possible by reducing temperature

Figure 4



Temperature variance reduction and tapping temperature reduction with AI-based temperature control. Predicting the entry and exit temperatures in primary and secondary metallurgy and recommending optimal temperatures for all stations live during the meltshop processing avoids unnecessary heating, reblows, process instabilities and cold ladle returns.

variations, which at the same time avoids other temperature-related disruptions during heat treatment. A side benefit of temperature control is an optimized scrap rate and quality at the BOF. It supports reducing energy consumptions and CO_2 emissions, too (Fig. 4).

These goals are achieved by integrating AI-based temperature control into the plant's level 2 and level 3 systems. This ML engine uses deep neural networks and other probabilistic models to predict optimal tapping, ordering, entry and exit temperatures for the BOF/EAF and for each secondary metallurgy stations. By considering more than 200 relevant features such as argon blow time series, temperature measurements, chemical analysis or ladle properties scattered across the heat's journey through the meltshop, the ML models allow temperature prediction for all sorts of different treatment routes between the converter/electric arc furnace and the casting machine. Internally, the models can be associated to different steel grades based on their chemical compositions, allowing quick extensions to new unseen steel grades for which no training data would otherwise be available and enabling transfer learning between the different grades. Also, the model tracks the heat states of individual ladles and their rotation within the plant to account for (missing) residual temperatures of the ladles.

First, each planned heat gets entry temperatures assigned with which it should arrive at the ladle furnace and caster after passing through the planned secondary metallurgy stations. Then, the interstation temperature prediction models compute the best BOF/EAF tapping temperature that is expected to meet those requirements. In a second step, the intrastation temperature prediction module computes an estimated tapping temperature once the main blow phase starts. This module takes into account various process parameters such as amount and composition of all additions like hot metal, scrap, slag formers and alloying, as well as blowing protocol and vessel condition. A similar model for the ladle furnace and degasser allows the operators to react quickly to the dynamic conditions deviating from schedule and ensure that the heat exits the station with the desired temperature.

Physical or empirical models usually get out of hand quickly when dealing with more than a handful of parameters. This is where the AI approach shines, as the large amount of accounted features allows for more precise predictions. In order to train the models on these large feature sets, historical production data covering more than two decades can be aggregated into the persistence layer of the software. Special training techniques thereby ensure that the model adapts to slow drifts or abrupt changes in the training data and hence automatically infers the relevance of training samples based on their age. Besides the historic data, the relevant level 1 and level 2 systems of the plant are directly connected to the software continuously updating the training data. This live integration is also used to implement a browser-based user interface for performance and prediction monitoring of the model from remote. Via a continuous data feed back into the level 2 system, custom integrations to the plant's operator HMIs can be implemented.

The training and evaluation of the ML models follow the standard best practice where the available data is separated into test and training sets. On the test set covering a selection of weeks over the last 18 months, the models reach a root mean square error (RMSE, average absolute deviation of measured vs. predicted) of ~3°C,[2] which is on the scale of the temperature measurement error itself. Following the predictions of the models, therefore, allows for the gradual reduction of the tapping temperature levels of heats arriving at the tundish by up to 10°C, depending on steel grade. At the same time, a positive impact on the cast steel quality by a more uniform solidification profile along the strand due to improved temperature homogeneity in the continuous casting process is expected.

Conclusion

This article described the requirements and potential solutions for a holistic vertically integrated optimization of the steelmaking process for flat and long products. The feasibility of the proposed solutions is demonstrated 24/7 as those applications are actively used in steel production at multiple plants, each with their individual product mix, equipment setup, peculiarities and data structures. Upcoming projects will transfer and extend the presented technology and software components to additional production routes of steelmaking.

Acknowledgment

Smart Steel Technologies thanks ArcelorMittal Eisenhüttenstadt and ArcelorMittal Duisburg for their collaboration in the works described in References 1 and 2.

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AISTech — This paper was presented at AISTech 2021 — The Iron & Steel Technology Conference and Exposition, Nashville, Tenn., USA, and published in the AISTech 2021 Conference Proceedings.