Eliminating CO2, Energy, and Quality Inefficiencies through Application of AI

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INTRODUCTION

Steel is the backbone of our modern civilization, but the production of one ton of steel emits an average of almost two tons of CO2. Therefore, the steel industry is responsible for about 8% of anthropogenic CO2 emissions. Due to rising average global temperatures, the resulting urgency to reduce greenhouse gas emissions is increasing rapidly. Especially the steel industry has understood the challenge of a fundamental and necessary transformation. Customer requirements have changed and the demand for carbon-friendly steel products is growing. Consuming industries such as automotive and aerospace are pushing themselves and their supply chains to reduce their carbon footprint. Growing investor and public interest in sustainability further foster the transformation towards CO2 friendly steel production.

The pressure to reduce CO2 emissions and energy consumption in steel production is therefore rapidly and legitimately increasing. Most of the direct emissions (Scope 1) in integrated steel manufacturing originate from coking, the sinter process, and the blast furnace process. Additional direct and indirect emissions (Scope 1 and Scope 2) can be associated with the melt shop and with downstream processes like reheating and rolling. The big lever in CO2 reduction lies undoubtedly in alternative steel making equipment, for example direct reduction plants based on hydrogen technology followed by EAF routes, also based on green energy. However, it will take several years before the new plants and alternative process routes make a significant contribution to steel production. Artificial Intelligence and Machine Learning - assisted production has the potential to lower energy consumption, increase yield and lower the carbon footprint already now, for existing plants and for newly constructed steel mills. In 24/7 production use, the software helps to minimize inefficiencies across various production routes. Each reduction of quality deviations, energy inefficiencies and CO2 inefficiencies minimizes the CO2 footprint of steel products.

Software solutions based on artificial intelligence and machine learning increase energy efficiency and thus reduce CO2 emissions along the entire process chain from iron ore reduction and liquid steel to the finished long or flat product. For example, they make it possible to reduce temperatures in the liquid phase through optimized processes, thus minimizing energy requirements. They also increase yield, so that more semi-finished products of prime quality can be sold with the same energy input, fewer coils are downgraded, and less scrap must be remelted. They improve the metallurgical properties of the steel and the quality of the surface. And finally, based on current process data, they precisely calculate the energy input and CO_2 emissions for each ton of liquid steel and for each product. However, isolated applications 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. To fully unleash the potential and increase artificial intelligence acceptance in steel manufacturing, the AI approach must be extended from individual processing steps to a plant-wide strategy. Establishing such an end-to-end optimization requires a systematic approach taking into account data integration, quality monitoring and process optimization. Also, the transition needs to take place in parallel with the existing steel manufacturing systems and must not interfere with ongoing steel production.

We have successfully implemented our artificial intelligence-based software modules in different steel mills, ranging from integrated via electric mills producing long and flat high-quality steel. They specifically target at improving the efficiency of the production process regarding energy consumption and yield increase by means of a Big Data-driven approach. In the following we describe how artificial intelligence-based emission assignment and tracking, temperature guidance, defect classification and casting optimization interplay to achieve this pressing goal.

DISCUSSION

Greenhouse Gas Emission Tracking

Implementing transparent CO_2 tracking in steel production is one of the major challenges to address, since transparent tracking of material in combination with machine learning allows for the assignment of accurate CO_2 footprints to individual pieces of material and their processing steps.

Therefore, a regression model was developed that tracks all parameters and, thus, correlates the total energy consumption to tapped hot metal. In this way the CO_2 emissions can be assigned to every single ton of hot metal. The model predicts all influencing parameters and their impact. This is the basis for a model that helps to reduce energy consumption and CO_2 emission.

Figure 1: Regression analysis

Process Control from BOF / EAF to Continuous Casting

Taking the entire steelmaking process into account, the optimum BOF or EAF tapping temperature is calculated by a global recommendation model for each heat in the sequence to precisely hit the specified ladle furnace temperature and tundish superheat temperature.

In order to tap exactly at the recommended temperature, the SST Temperature AI also calculates a prediction of the tapping temperature at the start of the refining phase (in the case of an EAF) or the main blow (in the case of a BOF), taking into account the numerous relevant input variables such as quantity, temperature and analysis of the pig iron, composition of the scrap, the refining phase schedule as well as addition of slag formers and other additives during treatment. This enables operators to react to any unwanted deviations. The treatment at the ladle furnace is supported by comparable models; in particular, the software also calculates the ideal discharge temperature.

The whole temperature guidance is not only optimized to save energy and CO2 emissions but to supply the liquid in the best suitable condition for prime- quality solidification to the casting machine. Therefore, the SST Temperature AI optimizes either possible route in even complicated secondary metallurgy processes, i.e., considers treatment and purging stands, ladle furnaces, vacuum degassers. The whole course of the temperature from BOF/EAF tapping to the caster is designed to save energy and CO2, time, and finally supply the ladle at the wanted temperature to the caster. The SST Temperature AI modules recommend the exit temperature for every single process step and guides operators to achieve the recommended temperatures.

In addition, the casting operation is supported by the tundish end-temperature model, which calculates the expected tundish end-temperature for the current heat during casting. The prediction is continuously updated in real time and considers, among many other parameters, the temperature of the preceding and the homogeneity of the current heat.

The interplay of these global recommendation and local prediction models stabilizes the process across all stations, so, for example, Marienhütte is now able to minimize temperature buffers and consequently, lower the tapping temperature in the EAF. On average, the temperature is reduced by 8K. The result is permanent energy and CO2 savings.

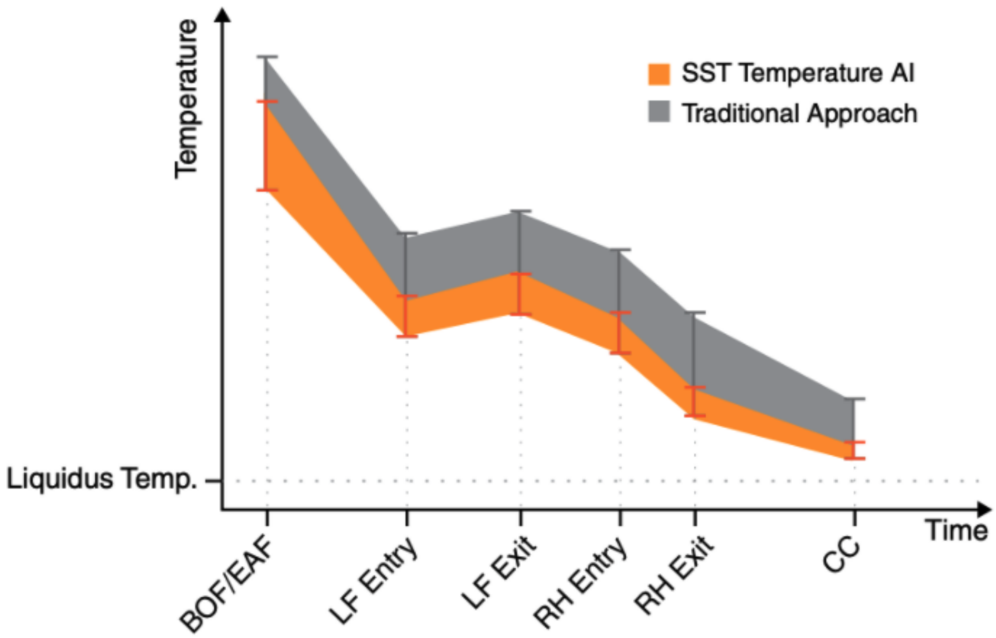

Figure 2: Minimizing Temperature Buffer

These models are successfully implemented and in 24/7 real-time operation in the basic oxygen furnace (BOF) melt shop at ArcelorMittal Eisenhüttenstadt and Duisburg in Germany and in the electric arc furnace (EAF) melt shop of Marienhütte in Graz, Austria. This proves that this approach is suitable for large and complex melt shops, but also for smaller plants and allows to increase profitability while reducing the carbon footprint.

Recommendations and predictions calculated by the SST Temperature AI are displayed within the original melt shop user interface as well as in the SST web-based human machine interface together with the most important influencing variables.

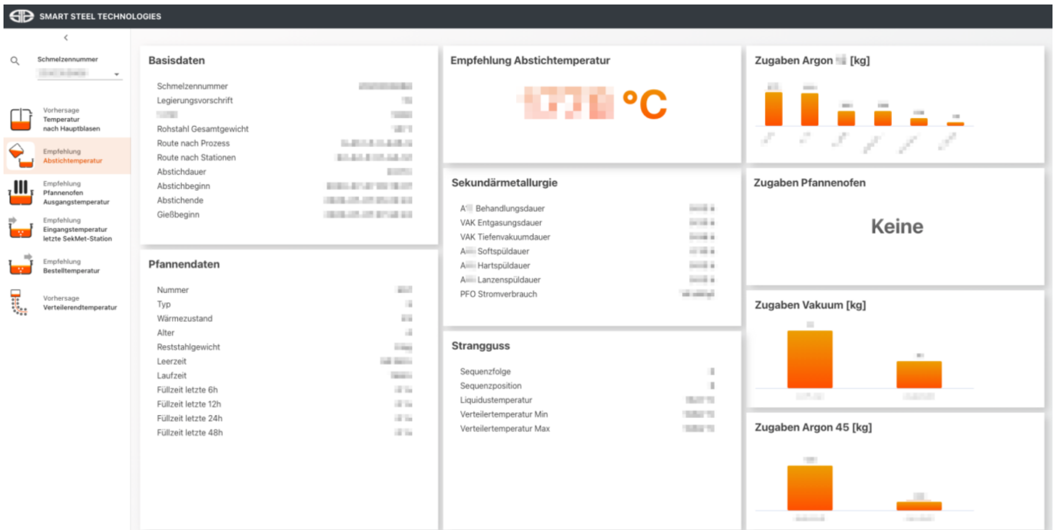

Figure 3: HMI for Tapping Temperature Recommendation at the BOF

Reliable Defect Classification

Additional optimization potential with AI algorithms lies in further downstream production processes where a clear optimization goal or “target signal” must be identified. Reliable defect classification in terms of quality data is the basis for process optimization. The main reason for rejecting material produced for high-end quality products, e.g., automotive exposed or electrical sheet metal, are surface defects, which in the worst case may lead to yield loss (if the material cannot be repaired or reapplied). This has a particularly high impact on the carbon footprint. Therefore, the reduction of these surface defects serves as an excellent target signal for process optimization, e.g., in continuous casting.

Steelmakers invest in 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. Due to outdated classification algorithms, most of the currently deployed ASIS classifiers are not robust and accurate enough to be used in automated process optimization.

However, we have achieved accurate classification using our deep convolutional neural network (CNN) classifiers specifically designed for steel surface images taken at individual steel processing steps. The network topologies of our SST Surface AI are fine-tuned with plant-specific training and test data and beat any other method in terms of labeling accuracy [6]. Integrating the full material genealogy (see section 2.5) enables potential defects to be cross-referenced to preceding manufacturing steps to achieve even higher labeling accuracy.

Data Integration and Human Machine Interface Implementation

Correctly classified surface defects from the automated surface inspection system (ASIS) are the mandatory basis for optimizing the casting sequence. In order to enable the machine learning models to calculate precise recommendations and predictions for each slab, the correctly classified defects which are detected on the finished strip have to be accurately mapped back to their position at the slab and thus, the parameters at the time of their origin. All relevant L1, L2 and ASIS data are integrated into the SST Data Platform in real time [5]. It aggregates and validates data from all sources in an integrated steel mill and stores data in specialized databases depending on the type and usage. This includes relational databases (scalars, genealogy), columnar OLAP databases (time series), a dedicated Vector database (features) as well as low-cost media storage (images, video). Any transformation occurring during the production process is stored during data aggregation to allow full material tracking and data transformation depending on the reference point.

Reclassified defects are shown in the web-based centralized coil map, including defect tracking, clustering, and full coil genealogy. The optimized casting schedule is also shown in a web-based user interface.

Casting Optimization

High quality steels used for automotive exposed products are specifically susceptible to surface quality defects such as slivers [3–8]. These defects often only become visible towards the end of the value chain. In previous studies we have shown how ArcelorMittal Eisenhüttenstadt reduced specific surface defects by more than 50% [2].

The input of the SST Casting AI is a full set of casting parameters, e.g., casting speed, submerged-entry nozzle, submersion level, mold width as well as melt shop parameters, such as superheat temperature and chemistry.

The models compute optimal values for continuous and discrete casting as well as melt shop parameters that lead to the best quality, e.g., minimization of slivers, while considering highly complex constraints originating from both business requirements and physical limits of the casting equipment. The system is operating in a 24/7 real-time mode.

The parameters are automatically fed back into the casting planning system. This results in an optimized sequence that minimizes quality deviations, and downgrading and reallocation. The yield increase translates directly into reduced Greenhouse gas emissions.

RESULTS

The overall temperature level from EAF tapping to LF exit was reduced by 8K. The result is permanent energy and CO2 savings. Surface defect classification was improved to 95% accuracy. Applying the SST Casting AI achieved a permanent reduction of the rate of sliver defects for automotive exposed grades by up to 50 % and more, and consequently less downgrading.

CONCLUSIONS

The presented solutions are actively used in steel production at various facilities, which all have individual product mixes, equipment setups, process peculiarities and data structures. By combining the different recommendation and prediction models, which support the process steps from the converter via the ladle furnace to the last station of the secondary metallurgy treatment, and considering the planned sequences at the casting machine, the SST Temperature AI allows precise temperature control during the entire secondary metallurgical treatment. Temperature-related disturbances are thus immediately reduced. In addition, the more precise control of the temperature leads to better plannability, also since, for example, treatment times at the ladle furnace are homogenized. We plan to further improve predictability by using off-gas data and chemistry data from taken samples for situations involving heats of high chemical energy (i.e., containing higher amounts of e.g., Cr, Mn, Si).

Reliable surface defect classification and mapping enables producers to implement data driven casting optimization with the SST Casting AI, leading to less scrap, rejects and reallocation.

Implementing such an integrated and systematic approach in a steel mill is a challenging project and requires close collaboration between metallurgy, steelmaking, data science, machine learning and IT experts. This cross-disciplinary expertise is the key to the success of such a project. The motivation to undertake the endeavor of implementing temperature guidance, defect classification and casting optimization is mainly economic. However, lower energy consumption, enhanced quality, and therefore increased yield, directly translate into the reduction of carbon dioxide emissions.

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