Optimized production of automotive steel sheet through application of AI

ArcelorMittal Eisenhüttenstadt permanently cuts down on surface defects

For the very first time in the steel industry, a substantial improvement of surface quality of automotive exposed grades has been achieved by precise process control through Artificial Intelligence and Machine Learning technologies. The main innovation is to not only predict surface quality, but to avoid formation of surface defects in the first place. Dynamic process optimization for each casting sequence, each heat, each slab is implemented based on methods from Artificial Intelligence and Machine Learning. The implementation and validation in production has been completed successfully at one of the most advanced integrated flat steel manufacturers in Europe – ArcelorMittal Eisenhüttenstadt. By **Dr. Ralf-Peter Bösler[1], Dr. Falk-Florian Henrich[2], Dr. Otmar Jannasch[3], and Dr. Jan Daldrop[4].**

Production of Automotive Exposed Grades at ArcelorMittal Eisenhüttenstadt

As an integrated flat steelmaker, ArcelorMittal Eisenhüttenstadt is a quality leader for automotive steel in Germany. Production facilities include sintering plant, blast furnace, BOF converters, secondary metallurgy, continuous slab caster, hot rolling mill, continuous pickling plant, tandem cold mill, two galvanizing lines and one coating line.

ArcelorMittal Eisenhüttenstadt produces hot-dip galvanized and galvannealed sheet featuring strong corrosion resistance, excellent working properties, and outstanding surface quality.

Ultra Low Carbon (ULC) and Interstitial Free (IF) steel grades for automotive exposed applications belong to the most important flat product categories.

ULC/IF grades for automotive exposed applications require highly accurate processing to reach the required quality levels. After tapping crude steel from the converter, precise refinement takes place at secondary metallurgy before continuous casting of slabs. Cast slabs are then hot rolled, pickled, cold rolled, and galvanized. **Fig 1**.

Alongside the manufacturing process, detailed inspections of chemical composition, mechanical properties, and surface quality are performed at multiple stages. Automated camera systems for top and bottom surface inspection are installed at the hot rolling, pickling, and galvanizing lines. Through advanced process control, automated slab and coil grading in combination with additional manual inspection, ArcelorMittal Eisenhüttenstadt ensures strict adherance to quality requirements for each customer order.

Ensuring highest surface quality standards in the production of galvanized and galvannealed ULC/IF grades, comes at high quality costs. Each time surface defects are detected the respective slabs or

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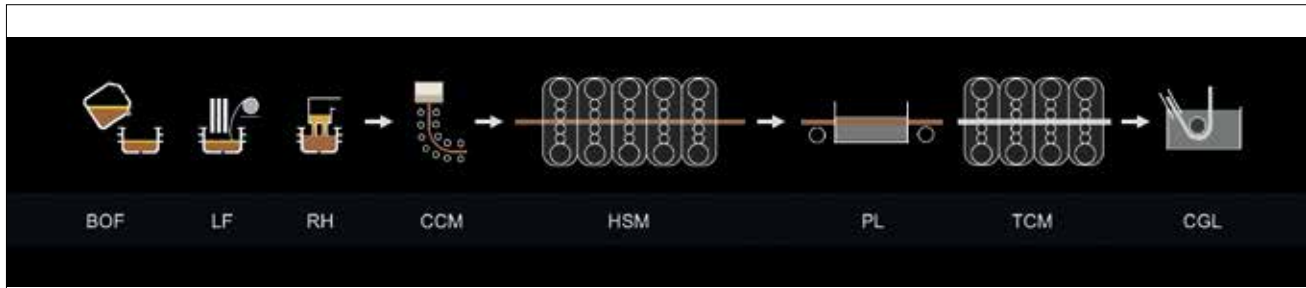
Fig 1: Process chain for galvanized strip

coils are downgraded. In the worst case, defects are detected only after galvanizing. Then downgrading takes place after high processing costs have been invested into the coil.

Prominent surface defects, namely centre slivers and edge slivers, originate from the continuous casting process. The underlying physical mechanisms that may lead to the generation of slivers as well as respective counter-measures have been studied intensively over the past decades [1-7]. By now, these methods of conventional process optimization have been exhausted. **Fig 2**.

During the past 10 years, data-driven approaches to the optimization of continuous casting quality have experienced only limited success. Typical problems include lack of process expertise in teams consisting only of data scientists and machine learning experts, lack of data, insufficient data quality, imprecise mapping of data from different sources, and mathematical complexities like the well-known curse of dimensionality.

Project set-up and execution
In order to speed up data-driven optimization against this background, ArcelorMittal Eisenhütten-stadt entered into a co-operation with AI company Smart Steel Technologies

Fig 2: Sliver defect on galvanized strip

(SST) in October 2019.

An overall reduction of sliver defects and related downgrading by up to 50 % was set as the goal.

The primary purpose of the project was not to predict or monitor surface quality, but to modify the continuous casting process such

that quality deviations are avoided in the first place. This goal was to be achieved without changing the continuous casting equipment. Implementation had to be completed within six months. Another six months had been reserved for detailed testing in production.

In March 2020, Germany entered into a nationwide lockdown to fight the COVID-19 pandemic out-break. Work had to be carried out from home offices. Digital collaboration tools replaced on-site meetings.

Despite these unexpected difficulties, ArcelorMittal Eisenhüttenstadt and SST completed the project successfully and on time. By the end of March 2020, all software integration and data analysis work had been completed. April 2020 marked the start of an extensive series of production tests.

Fast project execution was possible because ArcelorMittal Eisenhüttenstadt installed an effective project task force and because SST made use of its portfolio of ready-to-use software products designed specifically for continuous casting optimization through mass data analysis and artificial intelligence.

In August 2020, after completion of a large number of casting test sequences and subsequent rolling and galvanizing of the respective coils, the result was clear.

Fig 3: Deep convolutional networks for classification of surface defects
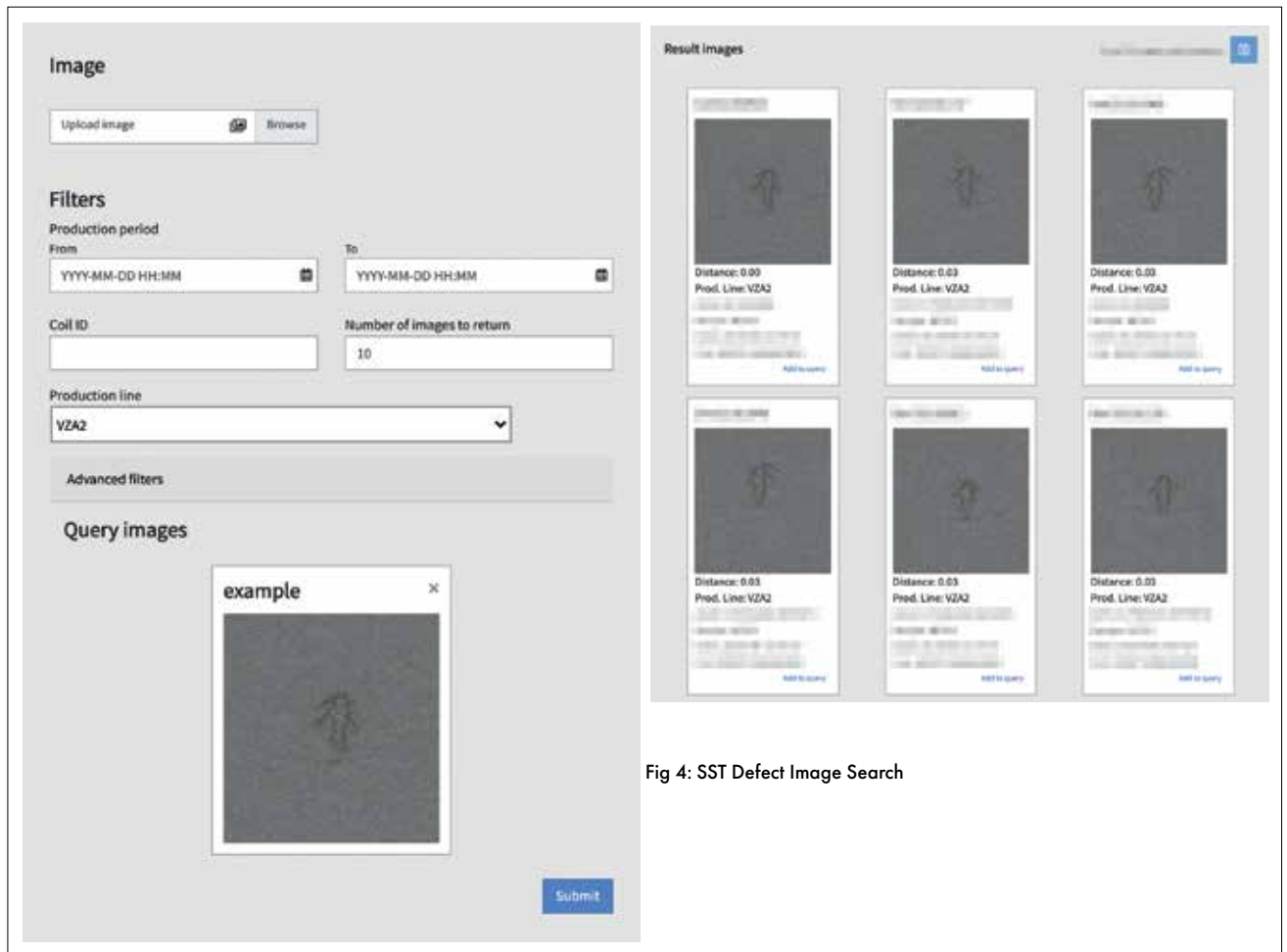
Fig 4: SST Defect Image Search

The rate of sliver defects had been cut by half compared to the average defect rates before optimization.

Robust measurement of surface quality

Robust, comparable, statistically significant quality measurements are a prerequisite for any approach to process optimization.

At ArcelorMittal Eisenhüttenstadt, automated surface inspection systems (ASIS) inspect the strip after hot rolling, pickling, and galvanizing. These systems automatically capture surface images of rectangular areas on the top or bottom of the strip that show irregularities. Many of these images of irregularities are irrelevant, for instance, water droplets.

The camera technology of most automated surface inspection systems provides sufficient resolution. But the automated classification of surface images into defect categories provided by typical ASIS lacks accuracy and is too unreliable to be used as a target signal

for process optimization. This holds true for sliver defects in particular as their appearance varies greatly.

Therefore, in the first phase of the project, SST installed its SST Surface Inspection AI software components at ArcelorMittal Eisenhüttenstadt's hot strip mill, pickling line, and at both continuous galvanizing lines. Precise and robust live classification of every surface image acquired by the ASIS systems is guaranteed through three specialized deep convolutional neural network architectures (deep CNNs) which have been designed by SST specifically for the classification of hot strip, pickled strip, and galvanized strip images[8]. **Fig 3**.
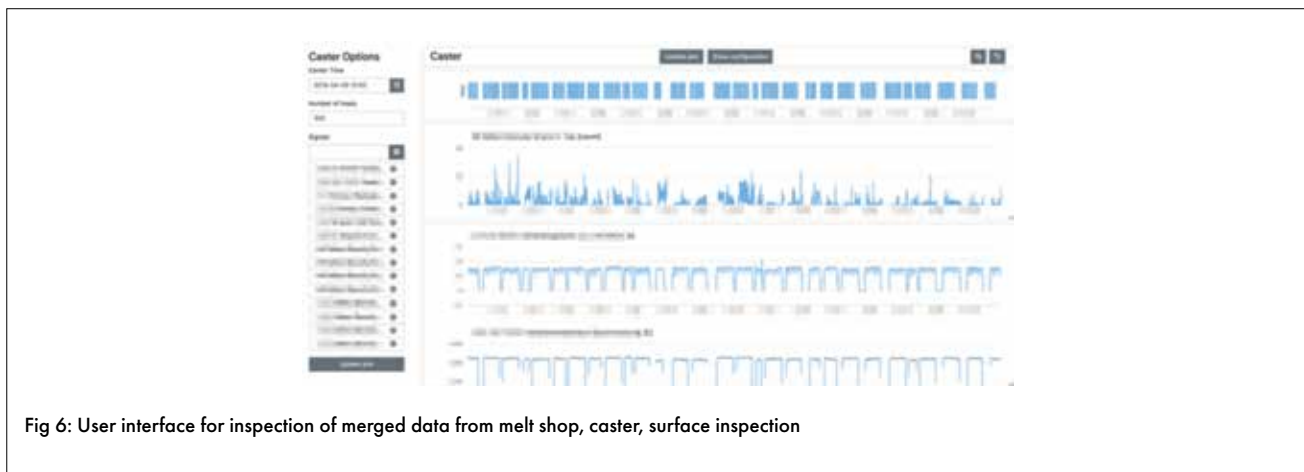
In order to shield the classification against false positives, the system automatically computes cross-process defect rates. The software classifies each surface image directly after the coil passes the respective ASIS. GPU-based servers installed at ArcelorMittal Eisenhüttenstadt's local data centre ensure a high processing speed.

SST installed additional support tools to facilitate day-to-day work with surface images and easy classifier tuning. This included SST Defect Image Search, a reverse image search engine that allows the user to specify a query image. The system then scans hundreds of millions of production surface images to return the most similar defect images within fractions of a second. **Fig 4**.

Using the SST defect classifiers, all new and historic hot rolling, pickling, galvanizing surface images from the last 18 months were classified into the correct defect categories, e.g., slivers, cracks, scratches, and so forth.

Through this approach, meaningful sliver defect rates were computed for the last 18 months of production. For each combination of steel grade, production line, and severity level, the number of such defects were computed per coil metre, coil-by-coil, day-by-day, week-by-week, month-by-month.

These surface defect rates, based on a precise classification of surface images, provided for an objective indicator of surface

Fig 5: SST Centralized Coil Map matches precisely all surface inspection results from HSM, PL, CGLs

Fig 6: User interface for inspection of merged data from melt shop, caster, surface inspection

quality and for a target signal for continuous casting optimization.

Cross-process data transformation

Using the SST Centralized Coil Map, a digital twin of each coil was created. The software system matches all surface inspection data and process data across all relevant production lines as soon as the data becomes available.

All surface inspection images and defect classification results from hot rolling, pickling and galvaniz-ing were mapped precisely into a central co-ordinate system. The algorithms take into account every uncoiling, upcoiling, flipping, cutting, welding, cropping, trimming operation along every production route, including inspection lines.

The result is a precise digital twin of each coil, computed automatically. The software displays the production path and surface defect statistics based on automated classification of all surface images using Deep Learning technology. Multiple display modes provide for quick analysis of all surface inspection results available for a given coil. Corresponding reports can be generated automatically. **Fig 5**.

In addition, SST's software was used to automatically merge surface defect rates with all Level 1 casting signals, such as casting speed, tundish temperature, cooling water flows and many more. Modern casting machines typically provide thousands of raw signals in varying tick frequencies from 0.5 Hz up to 50 Hz. While conventional systems only consider averaged values of process parameters, the actual time series have been used in this project. This is mandatory, because short spikes in signals (e.g., mold level deviations) contain valuable information. The actual Level 2 data of the continuous
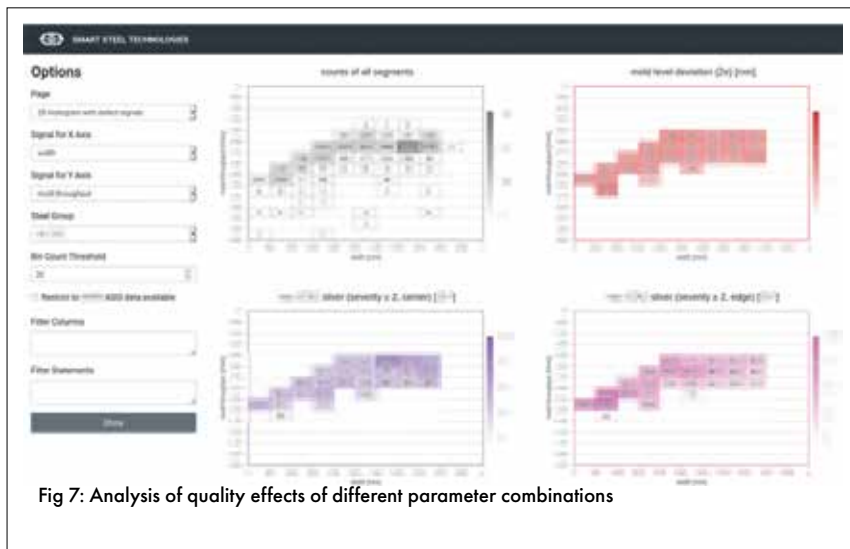
Fig 7: Analysis of quality effects of different parameter combinations

casting machine and of the melt shop (BOF, LF, RH) are merged in as well. The same is true for slab finishing data (grinding and scarfing information). The merged data is visualized for inspection. The user can choose production times and zoom into casting sequences. **Fig 6**.

Transparent insight Into quality-relevant data

Clearly, the raw signal data from the caster is still of limited use even after all relevant melt shop and surface inspection data has been merged properly. Therefore, the next step was to extract meaningful features from each relevant caster signal. For instance, a casting speed signal had to be disassembled into individual types of disturbances: manual speed changes, automatic emergency slowdowns, special speed ramps. Specific feature extraction modules for continuous casting data are used to fully automate this transformation of raw data into actionable information.

The process state of the continuous caster at a specific point in time depends on earlier and later (!) events. For example, a recent ladle change will influence the steel flow inside the tundish. Upstream events, e.g., a delay in secondary metallurgy, may cause a casting speed change. Therefore, all temporal and cross-process relationships must be considered.

Due to the process complexity, process experts need easy-to-use software tools that allow them to inspect all combinations of measurements and settings, that is, the feature space of the continuous casting machine. The SST Casting Analyzer depicted below allows users to select arbitrary combinations of casting and melt shop parameters, steel grades and operational data and inspect their effects on surface quality. **Fig 7**.

Automated optimization of process settings

The high-quality live data transformation described above forms the basis for automated data-driven casting optimization. The algorithmic core of SST Casting Optimization AI finds the optimal combination of casting and melt shop parameters with respect to surface quality based on historic data. The optimizer takes into account all relevant process constraints and uses a combination of metallurgical modelling and artificial intelligence.

Through live integration with the production planning system and MES of the melt shop and caster, an optimized casting sequence plan is computed dynamically for each production campaign. Through this automated, dynamic planning based on 100% of available historic data, optimal caster settings are derived for each individual slab, each heat, and each sequence. **Fig 8**.

Additionally, live models integrated directly into the melt shop's HMIs support operators of the caster itself and secondary metallurgy operators with live recommendations for settings to reach the highest precision in process control.

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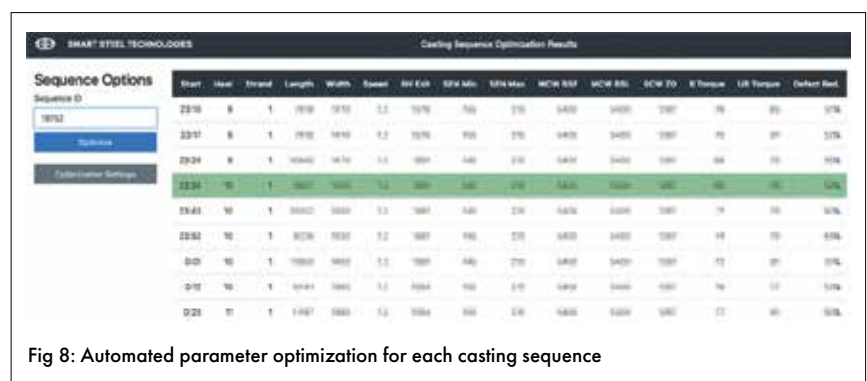[8] Classifying defects more reliably. Henrich et al. STEEL + TECHNOLOGY 2019 (4).

Fig 8: Automated parameter optimization for each casting sequence