Successful Use Case Applications of Artificial Intelligence in the Steel Industry

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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Steelmaking is a complex industry in which each process in the production chain generates a vast amount of data that can provide valuable insight when properly managed. Data originate primarily from hundreds of field sensors, then they are conveyed both vertically along the hierarchical pyramid of the plant automation, from level 1 to level 3, and horizontally through the supply chain. All these data contain information and represent the fuel that feeds all activities where knowledge buildup and consolidation is needed, ranging from the physical and metallurgical models up to the optimization strategies for production workflows.

Raw data, however, similar to fuel for engines, does not provide itself any information. Knowledge has to be extracted from data, hence the need to choose the appropriate tools to ingest, store, process and interpret data in a qualitative and quantitative way, a field that nowadays is popularly known as data science. As the complexity and number of components in production of industrial automation systems have been increasing, knowledge extraction from data plays a core part in transforming the industrial plant into an intelligent smart factory with the support of the latest digital technologies.

In the vision of Industry 4.0 evolution, machinery and equipment will have the ability to control and improve processes through self-optimization and autonomous decision-making, resulting in improvements in maintenance, supply chain, safety, remote diagnosis, real-time control with self-organized and autonomous management, transparency, predictability, effectiveness, and efficiency.

All the concepts listed above include artificial intelligence (AI) as an integral component for proper achievement. Danieli's strategic effort to include AI technologies in DIGI&MET products paves the way for an intelligent plant to optimize the resources and minimize the capital expenditure, thanks to a seamlessly integrated interface architecture across the vertical and horizontal levels of production in the domain of metals manufacturing.

Artificial Intelligence in the Steel Industry

The longstanding technical challenges, which to some extent are still persisting, such as rapid increase in the scale and speed of production, reduction of transformation costs through energy and process optimization, and high-quality products with value-added services, have resulted in deep analysis and usage of control and system technologies. These systems must adhere to accuracy requirements in order to meet strict specific standards for the production environment.

Steelmaking represents the perfect playground for an approach strongly based on data exploitation. On one hand, one has to deal with highly complex and multi-physics processes, where not all input variables and correlations are exactly known and where environmental conditions can change over time. On the other hand, process decisions are often made by operators, depending on their knowledge and experience. Instilling intelligence and knowledge into automation systems is therefore of paramount importance toward the achievement of the goal of a smart plant.

John McCarthy in the early 1950s coined the term artificial intelligence referring to "the science and engineering of making intelligent machines."[1] In general, however, it is extremely hard to define the term AI. What is nowadays commonly meant for AI is what is more appropriately denoted as "narrow artificial intelligence," that is the capability of a software/machine to perform certain specific tasks that in the past could only be carried out by humans. Popular examples are represented by natural language processing, image recognition, game playing, etc.

The interest toward narrow AI has seen an exponential increase in the last 10 years, mainly due to the widespread adoption of machine learning (ML). ML is a field of AI that aims at making machines "able to learn without being explicitly programmed" by automatically extracting useful patterns from data. Breakthrough innovations in data availability and computing power (graphics processing unit (GPU), cloud computing) lead ML toward the center of the transition to a new way of conceiving AI. Machines not only can learn to execute common actions like humans, but they can also think differently, such as finding patterns in high-dimensional data that the human brain cannot conceive.

ML and AI play extremely effective roles in the steel industry. First of all, AI can be used to allow machines performing all sorts of routinely based or dangerous actions that are traditionally carried out by operators, thus giving the opportunity to move humans to less risky tasks with more added value. Then, ML can be used to complement and enhance current process models. Classical models, indeed, are generally based on idealized systems and lack sufficient precision in complex tasks or dynamic environments. Physical models consider only specific sets of process variables, disregarding the information extracted from heterogeneous data sources. Under these circumstances, ML is very effective as the algorithms can systematically extract process relationships out of the data.

AI and ML indeed have been extensively applied in various fields of engineering including image processing, automatic control and data mining.[2,3] Some examples from literature are represented by a data-driven ML technique[4] to predict secondary deformation mechanisms in steel. An ML application methodology[5] to identify microstructures of steel based on crystallographic features obtained by electron backscattering diffraction; a novel method for steel surface defect classification[6] using ML techniques; a dynamic data-driven model[7] for predicting strip temperature in a continuous annealing line heating process; and an ML methodological approach for diagnosing cooling temperature deviation defects[8] that consists of four phases: data structuring, association identification, statistical derivation and classification.

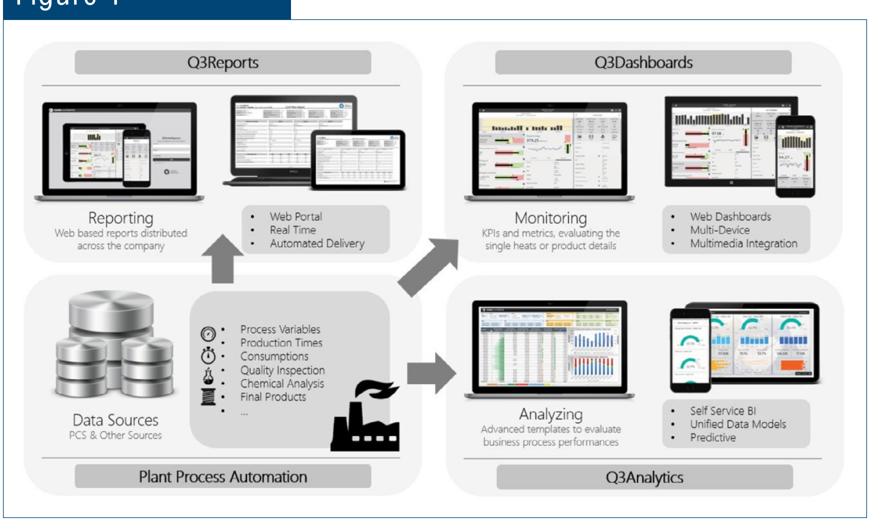
Industry-specific ML applications such as predictive maintenance, condition monitoring, process optimization and scheduling, inventory planning, pattern recognition, root-cause analysis, and smart management provide meaningful use cases where insight can be generated from the data to take appropriate actions with the target of minimizing CapEx and OpEx.

Danieli Machine Learning Architecture

Danieli Automation has developed a solution to foster a data-driven approach in the steel industry. This solution is based on Q3-Intelligence, a custom business intelligence platform for metals production. Q3-Intelligence is a data analysis framework that concretizes the revolutionary triggers of the data-driven era, data availability and data mining into the steel industry. The framework provides modules and features to extract data from heterogeneous sources across the plant and to store them in a unique and standardized access point, thus realizing the vertical and horizontal integration of information (Fig. 1). Later, to provide a continuous monitoring of the plant process and to feed the data mining process, information can be extracted from the raw data, converted into knowledge, and finally turned into actions.

Data integration and knowledge extraction are the pillars for the realization of the smart plant vision. The IT infrastructure, instead, must be considered a dynamic component, able to change and adapt to the technological transformations. For this reason, DIGI&MET has recently introduced a new architecture dedicated to ML models development and deployment. In fact,

Figure 1



Q3-Intelligence.

implementation of AI application inside the steelmaking environment poses a number of challenges that must be addressed. For instance, due to the complexity inherent in the process and to the vast amount of heterogeneous data generated, acquisition and analysis of big quantities of data from varied sources is a challenging task.

A modern steelmaking plant generates a huge quantity of data compared to the past, due to the increased number of sensors installed in all the areas of the plant, as well as to the presence of new types of data sources like video feeds or audio recordings. Based on their most recent installation experiences, the authors can reasonably suggest that a modern plant generates several terabytes of data per year. The biggest challenge for the business is to ingest data at a reasonable speed, enabling for further efficient processing, so that data are prioritized and analyzed to improve business decisions.

In order to overcome this challenge, the data acquisition and storage philosophy are based on the concept of a data lake. The data is stored in the same format as produced, or with minimal transformation before storage, eventually resulting in a shorter time frame from production to storage, with small resources required for the data acquisition step. Data is stored in raw format, therefore preserving all information, and processed at a later stage, allowing the flexibility factor for each different application. Data scientists can thus exploit this advanced data processing capability to analyze the data and develop ML models, e.g., for prediction or classification tasks.

The complexity involved in data management, design and development of ML algorithms, training and test processes, and information extraction from data according to the designed model requires high-performance computing infrastructures. For this reason, Danieli Automation architecture supports the use of computing resources from the cloud, in order to perform, in hours, processing tasks consuming weeks with a traditional architecture, reducing complexity and time and thus enhancing the benefit to the core business. The architecture is designed in such a way that the data transferred to the cloud is securely encrypted with a defined lifespan. This encryption ensures cybersecurity so that no one can intercept the data while being processed and the data is no longer accessible for other purposes once the algorithms are trained. This architecture (Fig. 2), realized in collaboration with leading service cloud providers with robust and secure services, has been successfully tested in several environments.

Architectures and applications based on cloud computing are still not widely accepted in the steelmaking environment and more in general in the manufacturing sector. The computational ability is an added advantage during the development phase, but it is often difficult to use during the production phase. The real-time process data is difficult to obtain during this phase as it limits the independence of the plant adding potential failure points that can lead to decrease in the production efficacy.

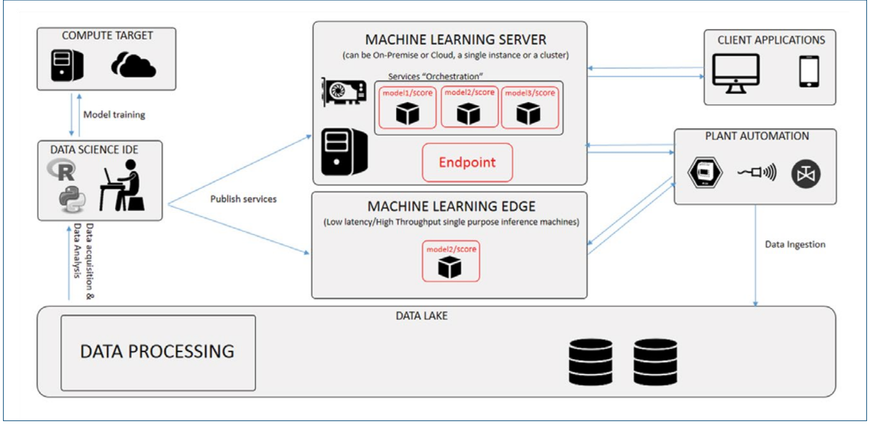
In order to overcome these hindrances, the Danieli architecture includes also on-premises modules, an ML server and an ML Edge. The first component allows running multiple ML models in the plant communicating with them through a web interface. Ensuring on-premises the same advanced inference capabilities offered by cloud providers, this solution guarantees a state-of-the-art service while maintaining the total independence of the plant automation network from the availability of an internet connection.

In order to use ML as part of fast automation control loops, however, this server is not enough, given the very low latency required to compute signals that are often sampled at high frequency. Hence, an ML Edge machine is added to the architecture for model deployment. These machines are small but powerful computers programmed to perform only the task of computing the results of a specific ML model with the minimal latency and the maximum throughput. This allows processing ML models in streaming mode, one sample at a time, even at very high sampling rates. These modules are completely independent and enable machines to become smart components.

AI-Based Applications

Starting from the analysis of the requirements of several customers, Danieli Automation designed, developed and deployed several applications based on AI. This section

Figure 2



Danieli machine learning (ML) architecture (on-premises and cloud).

discusses three recent use cases that provide a concrete realization of the concepts presented so far.

Q-CLOG — Q-CLOG is a predictive model for on-line estimation of clogging probability in continuous casting in advance respect to actual casting start, from the evaluation of process variables collected from scrap up to vacuum degassing (VD) treatment, in order to give in real time a decision support tool to the operator even before sending the ladle to the caster.[9] In order to achieve this target, a data-driven analysis was implemented based on data science processes for the assessment of the correlations existing between process variables acquired from the meltshop route and the tendency for clogging or erosion of the flow control devices in two casting machines.

Since a direct observation or measurement of the clogging level inside the nozzle is not possible with existing techniques, a method to detect the occurrence of the clogging event and to categorize the various heats produced, even from the past, based on their level of castability was provided. To analyze historical data, and to give a real-time indication of the ongoing clogging condition, an identification algorithm was developed based on process signals from the continuous casting machine (CCM) automation (Fig. 3). The clogging index estimated with the detection model is then used as a reference variable in a supervised learning classification problem. Preliminary steps such as data preparation, cleaning and analysis of involved variables with the support of process experts were carried out for the required predictive model. Defining clogging occurrence for a heat as the detection of a clogging level higher than a pre-defined threshold on at least one strand that was open during casting, it was found that clogging can be defined as a rare event since around 11.9% of the heats analyzed were hit, with some differences between the two casting machines.

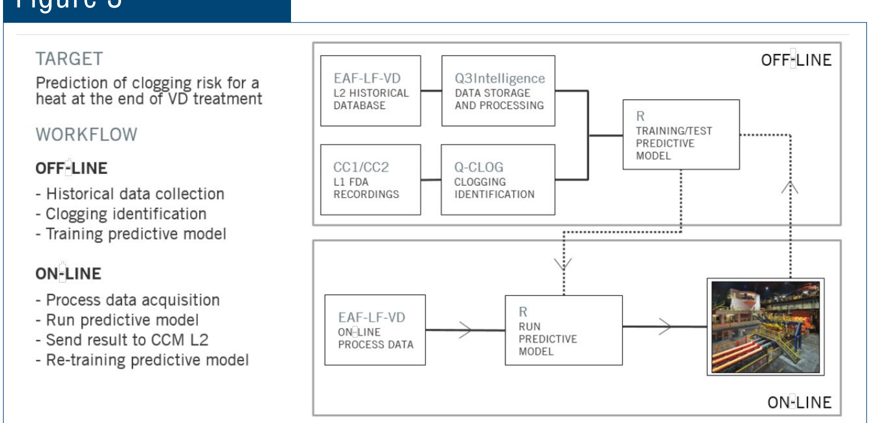
The probability of clogging events depends on the steel chemistry; one piece of evidence collected from the plant was the comparatively high incidence of clogging in re-sulfurized steels, as can be seen from Table 1.

Empirical findings have been transformed into requisites for the development of the model, with the definition of all the variables that can have an effect on the process and with special regard to those that can influence evolution of steel/slag equilibrium and non-metallic inclusions. For instance, operating practices are carried out during secondary metallurgy treatment with the target of improving castability, such as the addition of SiCa wire. All data related to those operations were recorded in Q3-Intelligence and then analyzed with dedicated tools. One interesting result of this analysis was that SiCa addition effectively reduces clogging occurrence, but the effect is different depending on the position of the heat in casting sequence and on the overall length of the sequence. This effect is clearly visible in Fig. 4, where the density distribution of SiCa wire added in VD is plotted for the first heat in sequence and for different values of casting sequence length. In the figure, heats with clogging are drawn in red solid lines, while heats without clogging in blue dashed lines.

Based on the above considerations, an input data set was defined using a mixed statistical-engineering approach. Due to the high complexity of the phenomenon and the possibility that process variables that are far from the caster can also influence on clogging occurrence, a process-based analysis was necessary to compile a preliminary list of potential candidate parameters for the model. This list was then refined with a data-driven analysis aimed at assessing the strength of the relationship between the parameter and the final clogging index; all the variables with a low level of relevance were removed from the data set.

A set of predictive experiments based on regression classification models was prepared where clogging

Figure 3



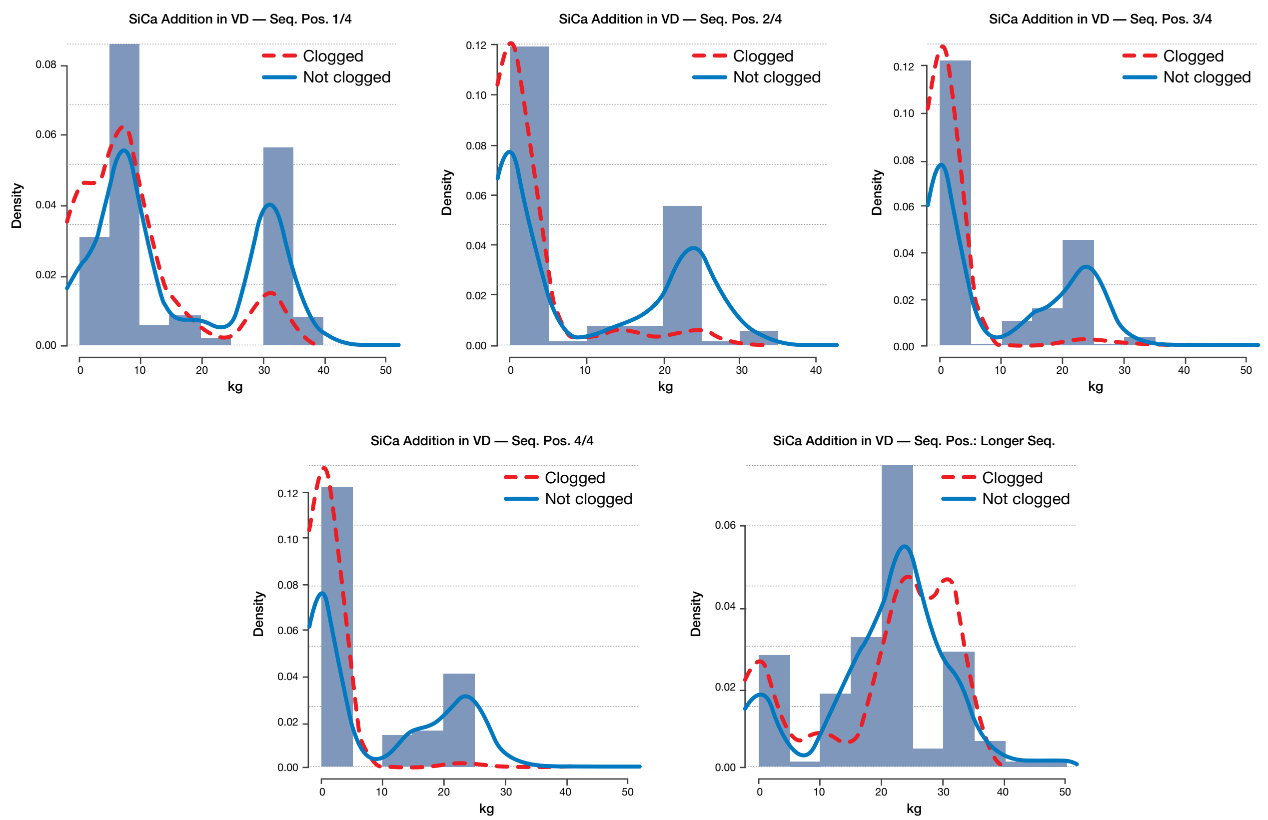
A schema of the clogging predictive model.

Table 1

Distribution of Clogging According to Casting Machine and Steel Type (21,927 Heats)

Steel group	CCM 1	CCM 2
High-S	16.40%	19.71%
Other	1.12%	2.80%
Total	8.60%	15.80%

Figure 4

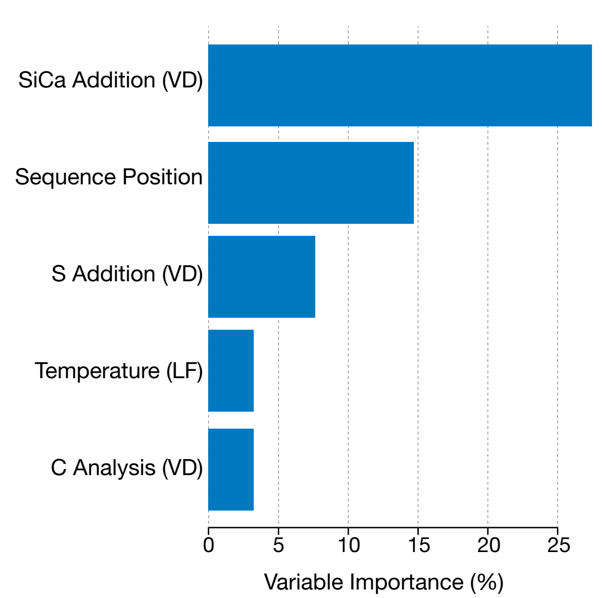


Effect on clogging of SiCa wire amount in VD for different casting sequence lengths.

presence was modeled on a set of process variables collected before casting start. The actual data set used for predictive model training is made of 50 process variables grouped according to different process areas and steps, chemical analysis, materials additions, temperature samples, processing, and ladle transport times. The variables have been measured on the entire set of more than 21,000 available heats from January 2015 and several classification models have been tested to find the best fit. In the end, the selected model was a gradient boosting classification that was found to be the most suitable to approximate the non-linear relationship between the list of predictors and the target variable.

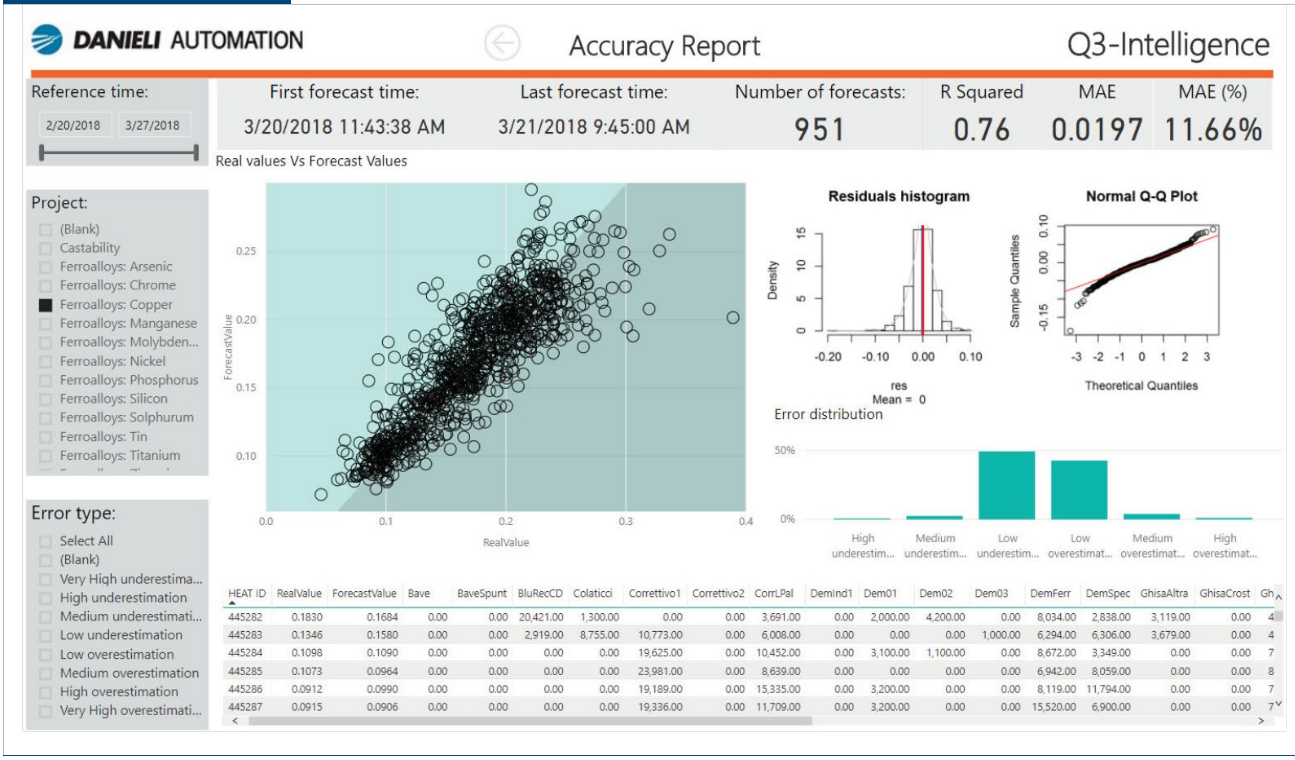
The performance of the model is quite good in terms of heats actually identified as potentially subjected to clogging, with an overall area under the curve (AUC) equal to 0.8. In detail, results are better in the prediction of events of clogging that involve at least 75% of the strands active in the caster: in this case, the model is able to identify 88% of clogged heats. Performance is slightly decreased when it is required to also identify heats with "light" clogging issues, defined as those with only one clogged strand. In this case, accuracy is lowered to 75% with the identification of clogging in 62% of the cases. The model also gave confirmation to

Figure 5



Ranking of variables in classification model.

Figure 6



Dashboard for real-time monitoring of predictive models accuracy.

most of the hypotheses reported from the literature[9] and the longstanding experience from the production site, such as the influence on clogging tendency of SiCa, Al, S and CaO additions, but also empirical findings from the plant, such as the difference in castability of steel produced from the two electrical furnaces present in the plant and the influence of production route and overall treatment times. In Fig. 5, a list of the most relevant variables is displayed, with a ranking defined by the number of times a variable is used in the set of classification trees.[10]

For the best management of advanced data analytics projects, the possibility for the data science team to monitor and evaluate the outcome of the predictive experiments is also of paramount importance. This was accomplished both through on-line services, giving the operator the necessary predictions to support operative production decisions, and on the other side with tools and services for continuous check and improvement of data quality and models accuracy. In Fig. 6, a web dashboard is presented to verify the model performance and to identify cases where accuracy was lower than expected and to supply useful feedback for data validation or model recalibration.

Q-TEMP VD — Q-TEMP VD is designed to show VD operators real-time information about the temperature of the steel during the degassing process. The application was created to provide a tool to measure steel temperature in real time using a contactless device. The idea is to employ a pyrometer to read the steel temperature through the open eye in the slag during the whole degassing process, from vacuum phase to atmospheric phase.

The usage of a pyrometer, however, is not sufficient, as it does not guarantee the desired reliability of the readings, since the signal is not available during some of the phases (at the start and end of the process, or during process deviations). In addition, there are moments in the process where the signal, even if available, cannot be completely trusted due to the erratic nature of the process itself.

This problem is solved by coupling the pyrometer with a temperature estimation model based on ML (Fig. 7), which uses data recorded from the process in the past to apply a correction to the real-time pyrometer reading.

Another AI functionality is the ability of understanding the status of the stirring plugs and quickly diagnose potential issues in order to help maintaining the maximum stirring and process efficiency.

The package also provides operators information about the normal working range of stirring plugs, and helps to identify deviations from the optimal process condition (Fig. 8). The application creates fingerprints of the normal plugs' behavior, described as a function that associates the flowrate to the pressure for every working condition.

Figure 7

Real-time measured and predicted temperature of the heat.

As Q-TEMP VD relies on the ability of the pyrometer signal to read the temperature of the steel, by pointing at a position where the slag has an open eye on the underlying steel bath, it is important to see and track this opening. For this reason, the model is able to detect the size and position of the slag open eye through real-time analysis of a video feed. This gives the system unparalleled precision in the estimation of the temperatures, while giving the operators a clear view on this part of the process (Fig. 9). This open eye detection is performed through image processing algorithms that are able to respond precisely and in a short time. The information about the total area of open eye can also be trended and used as an important variable to understand how the VD is actually performing and have a correct use of the stirring gas during the degassing phase.

It is important to note that Q-TEMP VD is a self-learning model. While it performs its estimation, it continuously records the data from the field and stores it to a database for later analysis. The model is able to detect a performance loss in its detection capabilities, which can be caused by a list of conditions that can change regarding how the process is executed, or in the production mix.

When the system finds such deviations from the optimal performance, it can use the most recent data to improve its knowledge of the vacuum degassing process and deliver the most accurate temperature predictions (Fig. 10).

Q-TEMP VD is currently installed in four plants worldwide and in all the installations the system is able to guarantee predictions with an error standard deviation below 5°C, which is the accuracy threshold usually required by the process.

AI for Surface Defects Identification

Machine vision plays a fundamental role in industrial automation, enhancing the flexibility of the machines making possible the recognition and the understanding of the content of an image without the intervention of a human being. Typical examples are related to process control, robot handling and quality control.

Figure 8

Comparison of output flow pressure fingerprint calculation for both plugs to the real-time plugs.

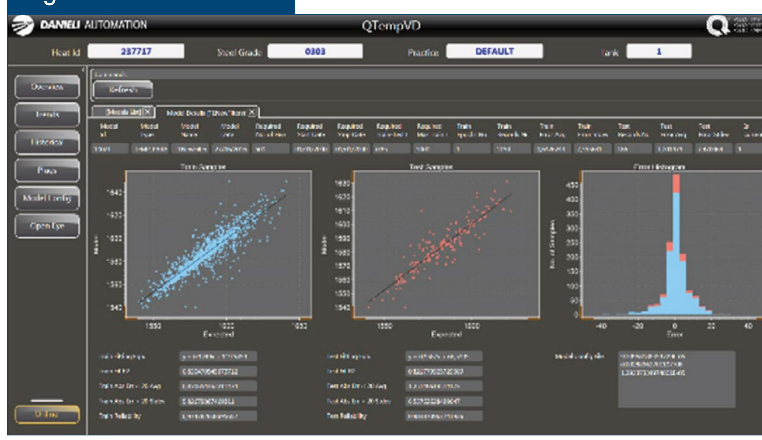
In recent years, the development of new AI techniques has contributed to a decisive improvement in the performance of machine vision applications. Thanks to the use of GPUs, the adoption of neural networks with very deep architectures (deep learning) has become feasible and more effective, determining the re-flourish of ML techniques in this field. These neural networks, if properly trained, automatically identify the fundamental features and the patterns that allow performing classification or identification of objects (features extraction). This scenario brings a paradigm shift in computer vision: ML algorithms, indeed, do not need to rely on very complex hand-crafted features and rules, but they extract relationships directly from data, in a way analogous to the learning process of humans. Mainly for this reason, deep learning, and in particular convolutional neural networks (CNNs), has proved to be particularly effective in image recognition tasks, reaching levels of accuracy in some cases higher than those of a human being.

One of the key applications for machine vision in the steel industry is the identification of surface defects in rolled and cast products. The defect detection is of fundamental importance for the quality control since it ultimately determines if a product is suitable for the market. Besides, the defect classification is becoming more and more important, making possible the correlation of the defects information with the process variables measured during production; the goal is to perform a root-cause analysis and eventually identify the origin of the defect, being able to intervene in real time, safeguarding the quality of the production.

Figure 9

OpenEye Image analysis algorithm.

Figure 10



Training performance of each ML model.

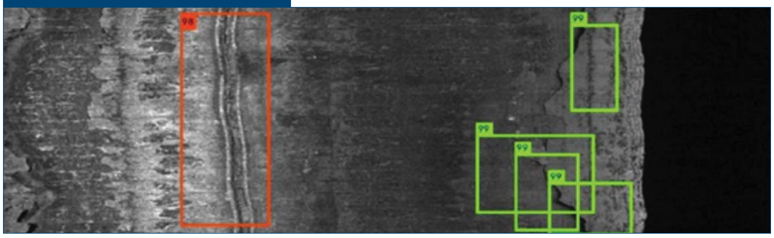
The classification of the defects proves to be more complex at the algorithmic level than the mere detection. This is substantial because it is not always straightforward to identify a set of rules or a physical quantity that allows discerning the type of defect, e.g., a scratch from a crack. On the other hand, an appropriately trained human operator can easily carry out these tasks. Deep learning wants to leverage this mechanism, which is to define algorithms that have a learning approach similar to that of human beings.

The following section discusses two recent case studies that address defects detection and classification by means of AI techniques.

Defects Classification From HiNSPECT Data — The HiNSPECT system is a product surface analysis system that automatically detects defects in wire rods and rolled bars during the hot rolling process from images collected in real time. The operating principle is the 3D reconstruction of the surface of the rolled product by illuminating it with two light sources emitted from different directions. This 3D reconstruction technique, known as shape from shading, allows surface discontinuities to be detected, therefore identifying and delimiting the defect.

In 2017, Danieli Automation began to test the use of AI in order to enhance the performance of the detection system, with the scope of lowering the number of false positives and to accurately classify the spotted defects.[11] The AI algorithm implemented a CNN architecture, which is able not only to classify a given defect according to a set of classes, but also to provide a bounding box for localization. Fig. 11 shows an example of how the CNN is able to accurately locate and distinguish two different types of defects.

Figure 11



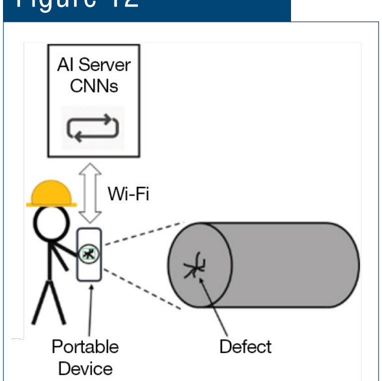
Defect localization and classification by convolutional neural network (CNN).

After about one year of testing, it was estimated that the CNN algorithm reaches an accuracy index higher than 85%, that is, more than 85% of the detected defects are correctly classified for each defect class. To reach high values of accuracy, however, as common to ML algorithms, large data sets of training examples are required. Also for this reason, Danieli Automation has decided to provide the AI module of HiNSPECT using a cloud technology. The working principle is as follows: the collected defect images are securely transmitted to the AI computing center. These images are then processed by the deep learning model, which checks the consistency of the defect, removes the false positives and classifies the defects according to the established classes. Results are then sent back to the plant and integrated in L2 or L3 systems. The system can support a cloud-based prediction thanks to the fact that only images of identified defects (through the 3D reconstruction) are sent to the AI service, thus limiting the data exchange over the web.[11]

A cloud-based AI classifier has several advantages with respect to an on-premises solution: first of all, it allows the computation complexity to move to a unique data center that can be appropriately industrialized to support heavy workloads; this relieves the customer from a high initial cost for the hardware. Moreover, ML algorithms can be constantly retrained on new images and made available in real time to the plant.

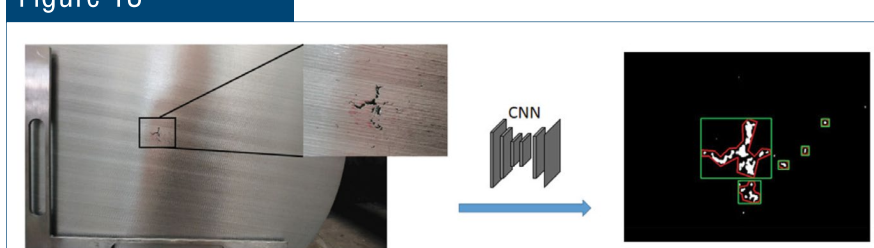
Defects Detection and Classification Q-VID Bloom Inspection (Q-VID BLI) — Independently from the image acquisition system, the same methodologies and algorithms can be applied to images coming from low-cost devices. On the one hand, the HiNSPECT is a high-performance measuring system, specifically designed for the defect detection in real-time quality control of a rolling mill production. On the other hand, defect detection and classification can be demanded during a quality spot check of the finished products, especially for big products, which are difficult to move, and where the control should be done by the operators walking through the warehouse. A significant test case is the quality check of blooms at the end of the casting process. In this case, the products are difficult to move and so a portable device, e.g., a smartphone or a tablet, can be profitably adopted to collect pictures around the warehouse. The quality control is made by operators who verify the presence of defects in the cross-section of the material. In the current workflow, the detection is based on a visual inspection and it is strongly related to the experience of the operator. Once the operator has identified the defect, the defect needs to be annotated on paper, which can introduce a possible lack of information and accuracy. To improve the accuracy of the annotation, by reducing the source of errors, it is possible to acquire images of the defected area by using a portable device. Then, once images are collected, AI techniques can be used to identify the position and the dimension of the defects. The algorithm that has been chosen for this task is again a CNN; for this particular case, the CNN is trained to solve a segmentation problem, i.e., the network is able to reproduce a mask

Figure 12



Scheme that represents the working principle of the application.

Figure 13



The image shows the segmentation of a defect as predicted by the CNN.

of the original image where each pixel is classified as belonging to a defective or a normal area. An example of the segmentation result is shown in Fig. 13. The CNN is trained using a set of images that has been manually segmented to highlight the defected area with respect to the background. Image augmentation techniques have also been used to enrich the training set. The segmentation technique has several advantages as it allows for the location, the size and the shape of the defect to be determined. The detected defect can successively be processed in order to be classified.

The designed solution is based on an Android application that guides the operator through the acquisition and the evaluation of the images. As the operator moves in front of the bloom cross-section, the application creates a target on the portable device that should be filled with the bloom area relevant to the analysis. The portable device takes a picture of the area to be analyzed and sends it, through a Wi-Fi connection, to an external server where the AI service is running. Fig. 12 shows a simple scheme of the architecture.

The results of the defects detection and classification are stored in a database and sent back to the mobile device. The information provided by the detection and classification algorithms are: (i) the number of defects in the analyzed area, (ii) the dimensions of the defects, (iii) the distance from the center and (iv) the class of the defect. An example of a defect detection is reported in Fig. 13. The contour of every single defect is highlighted and the area is boxed (Fig. 13).

Conclusions

AI, thanks to breakthroughs in data availability and computing power, is nowadays shaping a technological transition that affects a wide range of applications, from everyday activities to business and industrial operations.

The key concept of AI, and especially ML, is that software is able to extract knowledge from data. Machines can learn to perform tasks that humans can already do, but that were not doable by computers in the past. In this way, more parts of the production process can be automated. It is also possible to create or improve models that estimate or predict events by extracting information and patterns. ML is useful because such patterns are too complex to be easily detected by humans.

These technologies have an immediate impact on steelmaking industry and can help reduce operational costs, improve product quality, increase efficiency and ultimately grow revenue.

However, the steelmaking industry presents some very specific requirements in terms of automation and information technology, which pose some technological challenges to the adoption of AI, limiting the spread of such technologies.

A framework has been developed to integrate ML deeply into the existing automation systems, making it easier for steelmakers to adopt these technologies into their existing processes.

This framework allows Danieli Automation to exploit all the technological breakthroughs that are enabling ML, such as the storage of data in data lakes or the usage of high-performance computing on the cloud, while keeping the data private and secure and the plants completely independent from external services during production.

This approach allowed for the development of several applications of AI technologies for the steelmaking industry, some of which are presented in this paper. The presented solutions cover a wide range of problems in which ML can be applied, from advanced statistical modeling for prediction of events during the next production steps, to on-line process control through the calculation of hard-to-measure properties, to machine vision techniques to automate defects detection and classification.

All these technologies are already available and installed worldwide in plants that are pioneers in the realization of the intelligent plant.

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