Maintenance for Ironmaking Technologies Becomes Smart: The Power of Digitizing, Sharing and Linking Valuable, Empirical Knowledge

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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Digital transformation will offer huge potential to realize innovative, knowledge-based maintenance solutions and strategies. They will be the key for better use of resources to drastically reduce the time required for inspections and repair processes. This contribution aims to give insight into the most important challenge: Digitizing, sharing and linking valuable maintenance knowledge across operators and plants. Once this step becomes a success, smart maintenance will generate — beyond the hype — a significant added value and thus also ensure the acceptance in practical use to pave the way from fail and fix to prevent and predict.

Driven by the increasing global competition and growing pressure to maximize efficiency, digital transformation has gained momentum within the industrial sector. While applications of new technologies cover the entire life cycle of a production plant, manufacturing companies keep the focus on the commissioning, operation, maintenance and modernization of their plants. This paper puts maintenance of ironmaking technologies in the light of the digital age. It is addressed to all plant operators facing the challenge of optimizing existing processes in a meaningful way. Condition-based maintenance will be the key for better use of resources to drastically reduce time required for inspections and repair processes. The first part gives the reader an understanding of future maintenance and its possibilities. The second part will highlight overall requirements and their importance for a successful implementation and integration of new strategies into existing infrastructures.

The Evolution of Maintenance

Service and maintenance are essential elements of every manufacturing company. The overall objective is to ensure a long service life and reliable operation of the plant on the one hand, and to avoid unplanned downtimes on the other, thus achieving high plant availability. One of the main challenges is to efficiently implement maintenance and repair processes. Every single maintenance and servicing task is associated with costs, and the larger and more complex production facilities are, the more important it is to plan them as cost-effectively as possible. Depending on how a replacement affects the ongoing production process, several maintenance and servicing strategies are being considered.

Common Strategies — The two most common strategies are preventive and reactive maintenance. Reactive maintenance is performed when equipment has already broken down. Ideally, this approach should only be applied to parts that are easy to replace, less expensive and that do not affect the ongoing production process in any way. Otherwise, it is a far more costly strategy due to unexpected stoppages, especially as the unpredictable nature implies that workforce and spare parts may not be immediately available.[1] To avoid these risks, maintenance is usually performed proactively. Preventive maintenance — a periodically scheduled inspection — is intended to prevent breakdowns. However, decisions on whether an asset will enter the wear phase traditionally rely on general estimates and averages rather than on actual statistics on its condition.[1] It can be seen as a purely subjective strategy as frequencies of tasks to be carried out are difficult to measure. To play it safe, servicing tasks are usually carried out far too often and components are replaced even though they still work perfectly.

Nevertheless, it is not productive to send a technician to tend to a machine that does not need an action, nor is it efficient if a machine fails because it has not received the attention it requires.[2] To fully exploit the potential for optimization, the widespread use of information and communication technologies nowadays forms the basis for new condition-based strategies.[3,4] The overall aim is to carry out maintenance and servicing proactively — mainly condition-based rather than subjectively and periodically. This allows for optimization of the use of resources and keeping costs as low as possible.

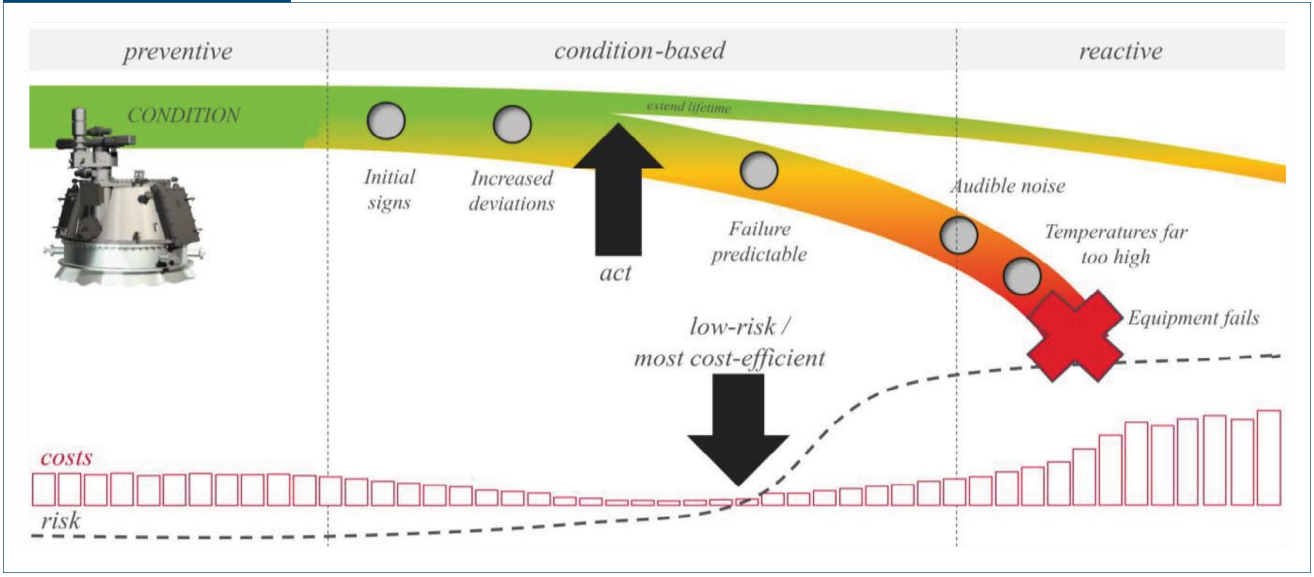
Condition-Based Strategies — The main challenge is to recognize initial signs in order to predict or even delay and avoid failures in the long term. Equipment usually does not suddenly fail or stop working. It will break down gradually, over a period of weeks, months and years. During this time, components will output numerous invisible warning signals (e.g., slight changes in vibration, functional behavior or general operation conditions). If these become perceptible for humans, it is usually too late and the wear is already too advanced.[1] The aim is to find the path between the most cost-efficient time and the moment before the risk suddenly increases (Fig. 1).

Condition-based maintenance (CbM) can be implemented on different levels of complexity. A distinction is made between diagnoses, forecasts and strategic analyses.[3] Diagnosis evaluates the current status. Performance indicators such as the efficiency, run time or capacity can be calculated. Afterwards, maintenance can be planned according to these results. This saves time and costs in a first step. If a plant is out of operation for a short period of time or is running on a lower capacity, scheduled tasks can be postponed accordingly. Furthermore, a diagnosis can uncover an inappropriate use of the equipment. Guidance for a proper use can ensure the maximum lifetime. Finally, diagnoses can also uncover deviations from the normal behavior, which can be an indication of potential failures.

Forecasting is the process of predicting the future condition in order to determine the remaining lifetime or remaining useful life of the equipment. The optimal time for maintenance can be regularly predicted to provide a helpful guidance next to the subjective decisions of the maintenance staff. These predictions have to be provided to allow enough time to arrange workforce and spare parts. Forecasting is also known as predictive maintenance.[4]

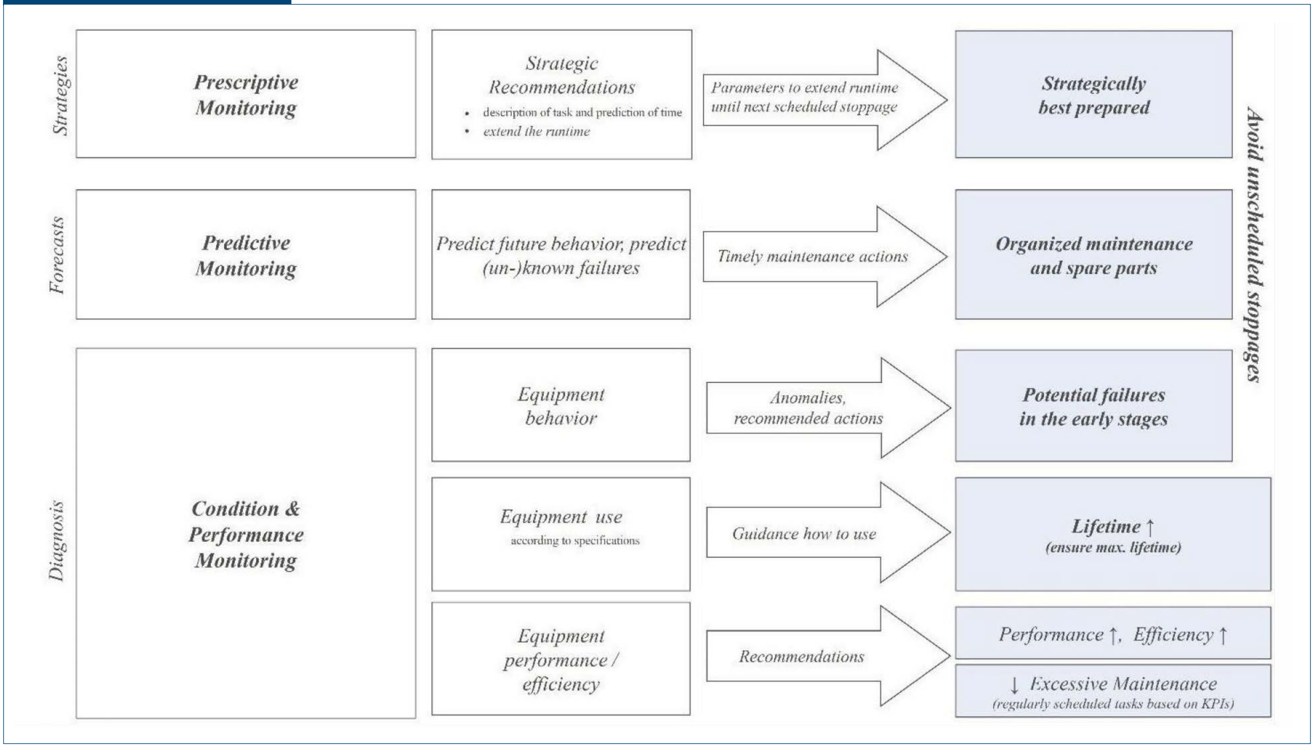
To reach the third level of complexity, potential root causes for failures have to be determined. Countermeasures can be taken before the failure occurs. This allows strategic planning of maintenance by postponing upcoming failures until a planned stoppage will take place. It is termed as prescriptive maintenance and allows the operators to be strategically best prepared. Fig. 2 summarizes the three steps of CbM.

Figure 1



Equipment life cycle and aim of condition-based maintenance strategies.

Figure 2



Condition-based maintenance on three levels of complexity: diagnoses, forecasts and strategic analyses.

Prerequisites and Technical Requirements

There is great potential for the optimization of conventional strategies. To take maintenance to the next level, a number of prerequisites have to be fulfilled. The following section summarizes the main requirements identified for data acquisition, knowledge extraction and knowledge provision.

Data Acquisition

- R-A1 Acquisition and storage of production data: Data is the raw material for further optimizations. They have to be aggregated from production facilities and disparate systems such as industrial databases, programmable logic controllers (PLCs) or Internet of Things (IOT)-enabled sensors. Open standards such as Open Platform Communications United Architecture (OPC-UA) enable an easy acquisition. Nevertheless, proprietary protocols are still present in older production plants and have to be supported.
- R-A2 Semantic description of acquired data set: A semantic description is beneficial to compare measuring points, machines and systems in log-term against each other. To facilitate a comparison, data can be assigned to individual role classes and relationships have to be modeled.
- R-A3 Data storage and access: To draw the right conclusions for maintenance optimizations, data needs to be processed, analyzed and compared in many ways. This leads to the requirement for a database that is optimized for the efficient storage and provision of measured values from sensor devices. Since the analyses will not take place at the control level, data must be transferred to a designated infrastructure using a suitable replication mechanism.
- R-A4 Capturing feedback from the operational side: Feedback from the operational side will allow data to be labeled and assigned to specific events that may have happened during operation. It will be beneficial for the later evaluation to not only gather production data from the ongoing operation but also direct feedback from the operating and maintenance personnel.

Knowledge Extraction — As described in the previous section, the main challenge is to make changes in the data visible. It helps to identify potentials for optimization, to uncover misuse of equipment or to detect critical failures before they occur. However, the most critical knowledge about equipment behavior, plant usage or frequency of failures is in the engineer's possession. Equipment can signal a large number of phenomena during operation that can be caused by different operating conditions or that can be a deviation from the normal behavior. Process and maintenance engineers are able to differentiate and can identify essential phenomena that may indicate an impending failure. This entails the following requirements:

- R-B1 Feature and knowledge extraction by the engineers: To make maintenance optimizations a success, engineers must have the possibility to independently digitize and capitalize their own knowledge without support of another programmer. Current approaches on the market mostly avoid this step and follow a semi-supervised or unsupervised approach without integrating valuable domain knowledge. Experienced staff must first interpret the importance and relevance of detected anomalies.
- R-B2 Digitizing knowledge for a wide range of use cases: Engineers should have the possibility to digitize any knowledge that can help to optimize maintenance. This should include for example:
  - The comparison of current conditions to historical baselines and averages as well as the classification of conditions according to well-known anomalies, patterns and failures.
  - The modeling of dependencies between anomalies to reproduce and link a sequence of phenomena to known failures.
  - The recognition of repetitive events over a defined period (remember and forget knowledge) in order to identify and prevent the reoccurrence of specific phenomena or failures.
  - The detection of short- or long-term trends of relevant key performance indicators (KPIs) and behaviors to inform or warn before a simple threshold is exceeded.
- R-B3 Integration of machine learning for advanced analysis: Machine-learning algorithms will strongly support failure detection or prediction.[5] Engineers should have the possibility to train artificial intelligence (AI) models intuitively. Depending on the use case, classical machine-learning techniques (for example, pattern recognition on uni- or multivariate data) or deep-learning approaches (using recent advances of neural-net architectures, such as RNN or LSTM for sequence modeling) can be more suited for the detection of emerging equipment failures. Before the training of the machine-learning algorithm, a data validation process in which the process engineers can apply their process knowledge to select and filter the relevant data for the use case is usually helpful to improve the performance of the algorithm.

Knowledge Provision — Once the knowledge has been extracted, it must be made available to the people who can benefit from it in daily operations. For this reason, the following essential requirements have been identified:

- R-C1 Sharing knowledge across all stakeholders: The extracted knowledge will create the most significant added value in optimizing the current processes if it is shared between all stakeholders who benefit from it. Information must be therefore tailored to different engineer groups and provided at different levels of detail. Knowledge should be easily accessible from anywhere.
- R-C2 Connection to existing computerized maintenance management systems (CMMS): Nowadays, the planning of inspection and maintenance work is managed by CMMS. They are designed to help maintenance staff in organizing tasks and spare parts as well as in carrying out maintenance more effectively by helping management make informed decisions.[6,7] The main goal of CbM is to optimize this planning in order to save time and costs. Extracted knowledge must therefore be directly integrated into these systems via appropriate interfaces. It allows the engineer to be strategically best prepared and informed for possible failures and breakdowns.

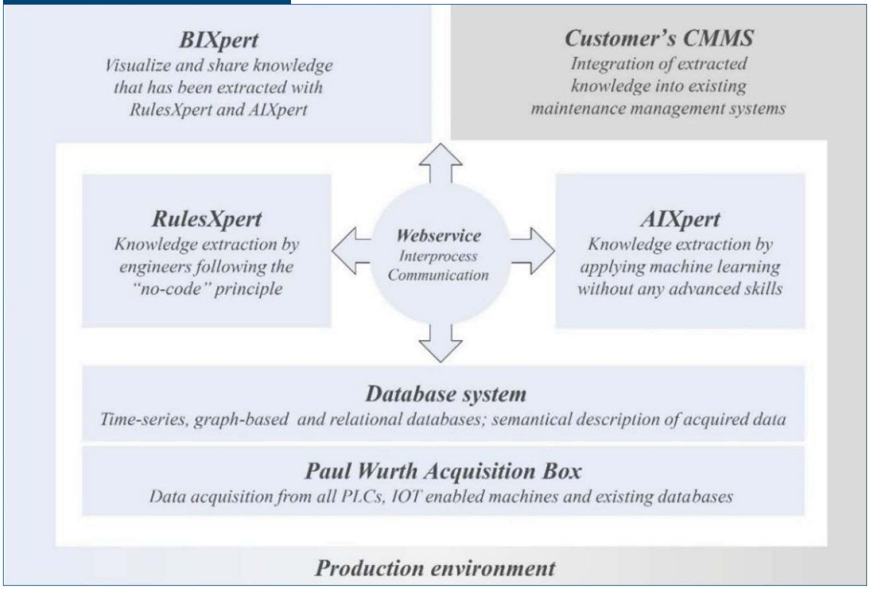
Key Technologies for the Implementation of CbM

As described in the previous sections, a successful implementation of CbM requires data as raw material on the first hand that can be used by a suitable platform for extracting and sharing valuable knowledge by and to all experts and engineers. In light of Industry 4.0, Paul Wurth combined its process knowledge and mechanical expertise with the skills of developers and data analysts within the in-house startup incubator to develop a tool kit for engineers that fulfills the requirements mentioned earlier. The tool kit supports the engineer:

- To acquire and store production data from all PLCs, IOT-enabled machines and databases. Data becomes intuitively accessible, which is facilitated by a semantic description of acquired data sets, and can be used isolated from the production control for process and maintenance optimization.

- To digitize and capitalize valuable process and maintenance knowledge that has been gained about the production. It will not only enhance CbM, but will also allow building up a knowledge base of know-how over decades.
- To share acquired knowledge from one site to another in order to compare machines, plants and factories. Once a knowledge base has been established for a plant and CbM has been implemented, it can be easily scaled up to other similar equipment and plants.

Figure 3



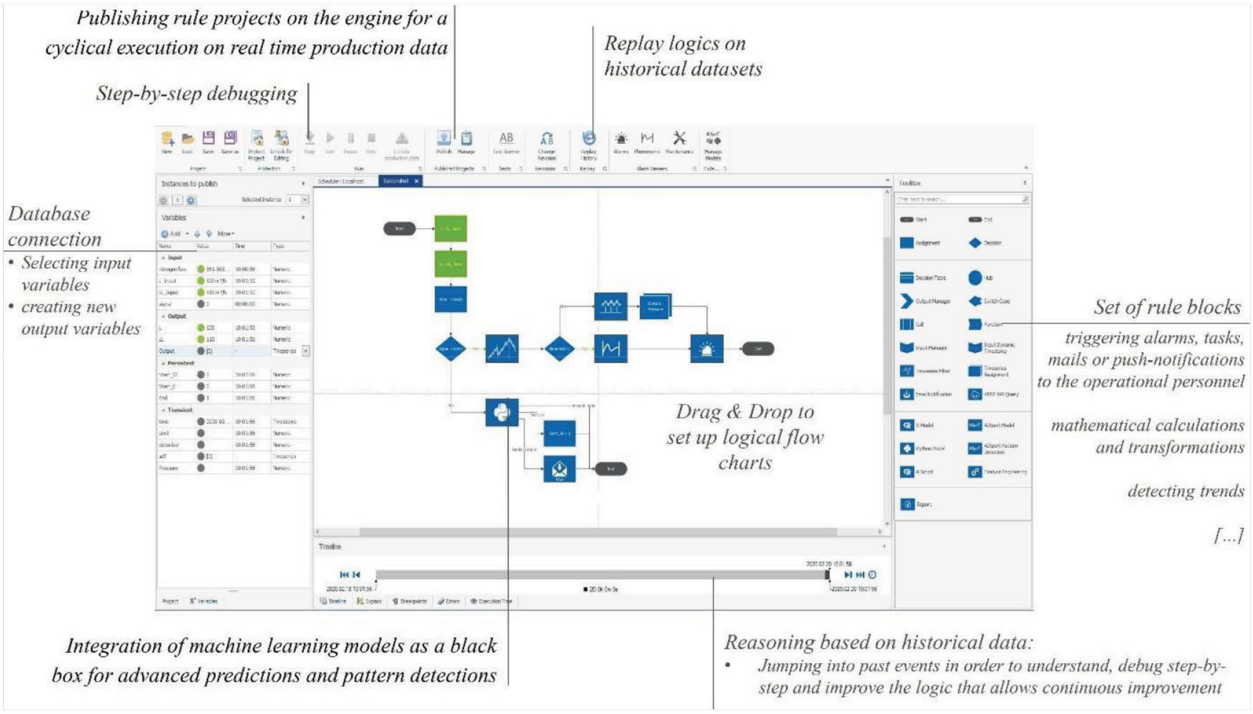
Key technologies for the implementation of CbM.

Key technologies that have been developed and that are being used in order to take maintenance to the next level are visualized in Fig. 3. They will be described within the following sections. Since the most important step toward CbM is the knowledge extraction, the following section focuses on the two developed software modules RulesXpert and AIXpert. The I.T. infrastructure and data backbone, embodied by the Paul Wurth Acquisition Box and dedicated database system, have already been introduced in Reference 1. According to the requirement R-A1, it acquires data from databases, PLCs or human-machine interfaces (HMIs) – independently of its format and of the communication protocol that has to be used. By fulfilling this requirement, data is semantically described, classified and, according to requirement R-A3, persistently stored. Depending on the type of data, it is either stored in a time series, graph-based or relational database together with meta information. A web service provides a level of abstraction and uses the metadata to facilitate data access and communication between higher-level tools and applications and the databases.

Knowledge Extraction With RulesXpert — RulesXpert is the core environment for knowledge extraction. According to requirement R-B1, it is implemented as a zero-code platform to define business logic without any programming skills. RulesXpert allows domain experts to create, test, debug, publish, continuously execute on real-time sensor or expert model data, and to supervise and continuously improve rule-based logic to automate their process knowledge or maintenance expertise. It empowers maintenance engineers to make use of their in-depth knowledge about their equipment by providing an easily accessible and safe way to implement rule-based logic into the level 2 automation system. RulesXpert provides a user-friendly platform that enables rule design, requiring no conventional coding skills, such that no automation or I.T. engineer is required to create a real-time digital recommendation system. This allows domain experts to rapidly create new level 2 functionalities and significantly shorten the development time versus conventional software approaches. Thus, RulesXpert responds to the need for continuous improvement to better market competitiveness and safe operations. The scope of the process and maintenance rule projects is according to requirement R-B2 very broad, covering, e.g.:

- Mathematical calculations and transformations, e.g., for the calculation of use case–specific KPIs.
- Inference of recommendations and triggering alarms, tasks, mail or push notifications to the operational personnel.
- Detection of phenomena and short-term, middle-term or long-term trends of equipment conditions.
- Reasoning based on historical data to compare conditions to historical baselines, averages or sums and to detect repetitive events or the reoccurrence of detected anomalies.
- Classifications of conditions according to well-known anomalies and patterns.
- Integration of machine-learning models as a black box for advanced predictions or pattern detections.

Figure 4



Graphical user interface of the no-code platform RulesXpert and its key features based on the requirements R-B1 and R-B2.

The RulesXpert module consists of two components. First, a service that coordinates a rule project execution on real-time production data from one or several data sources: Each project execution creates a log entry into a database that allows tracing individual executions and provides historical diagnosis. Second, a graphical user interface to design, test and debug a rule project. It provides access to one or several RulesXpert engines running in the background and allows publishing a rule project to the service engine while continuously monitoring that execution. The main purpose for the designer is to do off-line experiments until the desired logic is captured (Fig. 4). Before a rule is published to the scheduler the rule can be executed on historic data to evaluate the logic on past process phenomena.

The platform comes as a data source–agnostic rule engine by default. The definition of the nature of the data sources (one or several) is implemented via extensions or plugins that can be dynamically loaded into the RulesXpert designer and engine. This guarantees a high degree of flexibility regarding the choice of data source (e.g., SQL database, data historian, OPC UA), such that plugins can be developed to fulfill very specific requirements. RulesXpert provides a set of generic rule blocks by default, which can be further enriched using the same concept of plugins. This allows developing plugins adding tailor-made rule blocks required by specific maintenance scenarios. By using the toolbox pane, the engineer can choose between a various set of rule blocks. They can be moved by "drag-and-drop" onto the diagram in order to set up logical flow charts. The list of available function blocks can be extended by loading plugins and importing more advanced or tailor-made rule blocks into the system.

The no-code platform can also deploy machine learning models generated using AIXpert (see section above) or using custom machine-learning models and scripts developed in Python or R. When querying a model, data from variables of the rule project is sent to the model and the returned results are again assigned to project variables. As such, the external models can be used as conventional rule blocks in a control flow. This allows for security mechanisms to be implemented around machine-learning models to control either which model is triggered based on the system condition or to cross-check the output in case of unusual prediction values.

A major advantage at the same time is that logics can be validated at different points in time, e.g., on historical data. A time marker defines the current time for the rule project. The main benefit of this timeline is the possibility to jump into past events in order to understand, debug step by step and improve the logic. If, for example, an error occurred in the past that a rule logic would like to predict in the future, the engineer can jump back to the past and validate the rule. If the engineer is satisfied with the rule design, he can publish the rule project on a RulesXpert service engine. The engine will execute the project cyclically on real-time production data or can be triggered on event from any other application. A scheduler displays all rule projects that have been published on the RulesXpert engine.

Applying Machine Learning With AIXpert — AIXpert is a module according to requirement R-B3 in order to apply machine learning without advanced knowledge or specialized skills. The engineer can intuitively train models for failure predictions or apply pattern recognition, e.g., to detect well-known equipment failures. Trained models can be easily integrated as a rule block in RulesXpert to execute the model on live data.

Pattern detection is one of the key features that can help the engineer to label essential features in the data, combine them across different signals and link a set of patterns to specific failures. The goal of the development was to enable advanced pattern detection with machine learning which cannot be easily described with rules. In the hands of an experienced engineer, these algorithms can provide solutions to difficult problems and do not require knowledge about the algorithm itself. In a first step, the engineer selects a univariate pattern in a time series and assign a label to it. This functionality allows manual labeling of abnormalities in sensor signals. To test and evaluate pattern detection directly on historical data, they will run a set of detection algorithms (e.g., Dynamic Time Wrapping, Euclidian, SFATrie). It will help to find the same phenomena in the past, to label historical data sets and draw conclusions from the history. The trained algorithm can be exported afterwards as a rule block for its deployment in RulesXpert (Fig. 5).

Once the step is done, the engineer can also, in a second round, use the historic data and the created labels as an input for another algorithm, which could be dedicated for root-cause analysis. This facilitates the identification of causes and prediction of failures. The engineer can, depending on their knowledge, either configure the prediction model structure or follow an automatic approach to let AIXpert automate the training with the help of a dedicated algorithm searching for the best neural network architecture and results. Following the manual learning, neural networks are defined layer by layer, meaning by specifying the type of layer (e.g., Feed Forward, Linear, GRU, LSTM, RNN), the activation function (e.g., Linear, sigmoid, SinE, TanH, Lecun, TanH) and the number of neurons of that layer. The second option is known as automated machine learning (AutoML). The most appropriate architecture will be chosen automatically and an automatic overfitting detection considers the number of consecutive rounds where the loss function in the test data set has a positive slope.

Finally, the engineer can export the trained model for live deployment in production with RulesXpert. The engineer has the following advantages with deploying machine-learning models within RulesXpert:

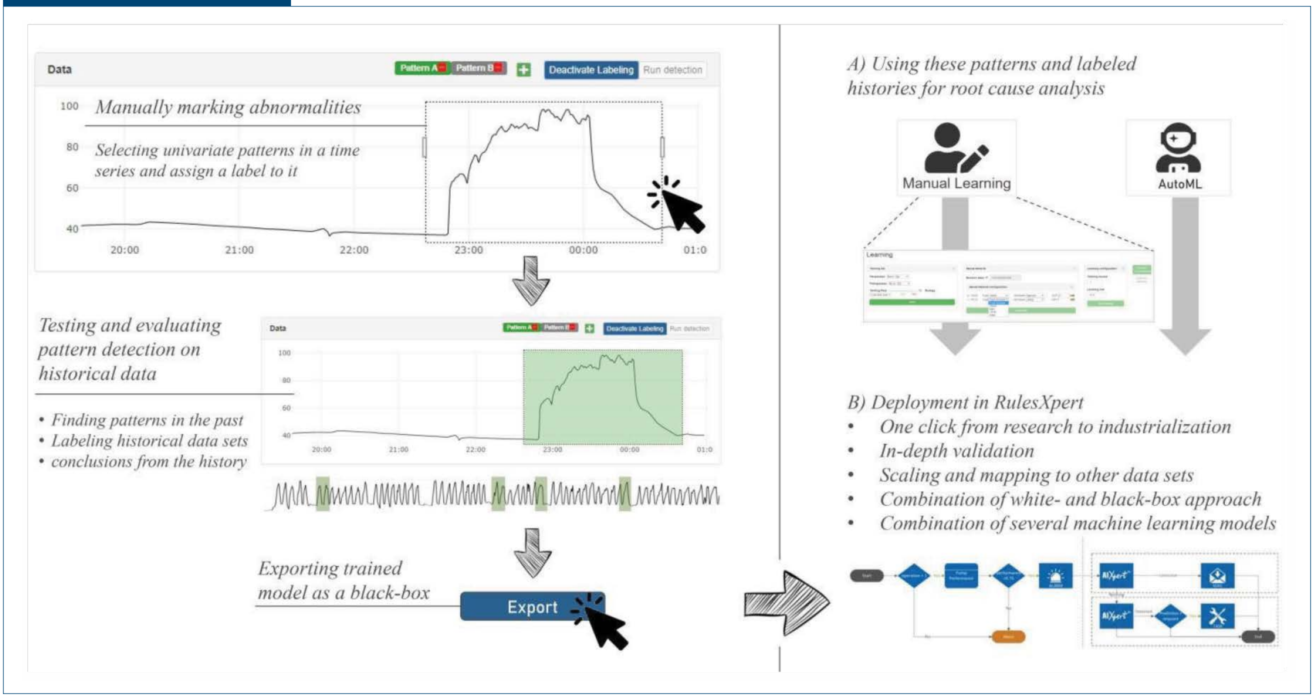
- One click from research to industrialization: Machine-learning models can be transferred directly from the development environment into production to support decision-making on live data.
- In-depth validation: Validation by an experienced engineer is important to ensure acceptance by using black-box models. RulesXpert allows a detailed model validation by exploiting the full range of functionalities mentioned earlier.
- Scaling and mapping to other data sets: Once a model is trained for a particular use case, it can immediately be tested with other data sets to scale it to similar cases.
- Combination of white- and black-box approach: While RulesXpert follows the classical white-box approach and AI models are termed as a black box, the mix of both is particularly powerful. Well-defined rule logics can be gradually enriched with advanced algorithms and are not being replaced by pure black boxes.
- Combination of several machine-learning models: In some cases, only one model but also a set of models may be helpful to detect anomalies. A combination of defined patterns may give better hints or predictions than a single model.

Extracted knowledge can either be stored, visualized on dashboards, integrated in existing CMMS systems or shared via reports. A reporting plugin within RulesXpert also allows, for example, generating condition-based reports based on templates, rule project variables and tabular data. Furthermore, the module BIXpert (Fig. 3) allows the engineer to build own dashboards on a web-based user interface. A set of industrial, customizable panels have been developed in order to avoid coding.

Examples Out of the Ironmaking Industry

The following section provides a brief insight into some use cases for CbM on ironmaking technologies. The implementation is based on the key technologies mentioned above and has been driven by the experienced maintenance and process engineers. The blast furnace casthouse machines and Bell Less Top

Figure 5



Graphical user interface of AIXpert and workflow for the use of pattern detection.

charging system are taken as examples in the following sections.

Condition and Performance Monitoring for Casthouse Machines[1,8] — The analysis of casthouse machinery data gives a precise insight into the tapping process itself and how the equipment is being used. KPIs such as the number of casts per day or the time between two casts can also be determined by other methods, however more advanced insights such as the actual length of the taphole or the actual clay volume being injected will provide a new level of information to the operator. The observation of various process values (e.g., taphole length, used clay volume, time between two tapping operations, air inclusions in the taphole channel) helps to give guidance to the operating personnel. The precise determination of the taphole length can be used, for example, to give advice to the operator about the optimum amount of clay to be injected. This value can be directly applied through using the equipment in automatic mode. A set of advanced KPIs and phenomena detection furthermore optimizes the drilling and plugging processes (e.g., the duration of the drilling processes, the effective use of the hammer unit or operational reliability of the blast furnace, consumables used over time). The use of historical data is particularly helpful in this context.

The condition and performance monitoring includes furthermore the monitoring of machine functionalities (e.g., long-term changes of parameters such as slewing pressures) and the monitoring of the operating time of main components (e.g., hammer unit, cylinder and motors). With the hammer and rotation motor being the key components of hydraulic taphole openers, it is crucial to monitor their operation. A high proportion of "drilling without hammer" in the "total drilling time," for example, shows that the use of the hammer is limited to the hardest part of the taphole. These parameters need to be closely monitored together with the total drilling time of the taphole opening, as the latter has to be kept within acceptable limits for a reliable and safe blast furnace operation.

Finally, the advanced monitoring will extend the knowledge for operation and maintenance benchmarking, e.g., between different equipment setpoints, tapholes or shifts. Comparing performance data between machines at different tapholes, different blast furnaces or different production sites can either detect local improvement potential or confirm the competitiveness of the individual operation. Benchmarking as part of the condition and performance monitoring is a valuable tool for optimizing equipment performance. Semantic descriptions, as mentioned in requirement R-A2, have proved to be fundamental and useful for this step.

The advanced data analysis is also dependent on the feedback from operating personnel. According to the successful implementation of the requirement R-A4, troubleshooting, on the one hand, it is now no longer limited to the personnel on site and feedback can be directly integrated by the engineers to enrich the system with more knowledge.

Condition and Performance Monitoring for Bell Less Top® Charging System — The condition and performance monitoring system is a result of efforts aiming to continuously increase availability and ensure optimal performance of the Bell Less Top (BLT) equipment. The system is based on Paul Wurth's experience as an OEM in the field of blast furnace charging systems. Based on the integrated knowledge of experienced engineers, the system applies signal processing to evaluate equipment behavior. The main objective is to provide the ability for customers to improve their understanding of equipment state autonomously and to provide a solution as a strategic component for increasing blast furnace top charging system availability and reliability. This includes, among others:

- The verification of the valve opening/closing times for all vales, e.g., the upper and lower seal vales, the material gate, and the equalizing valves.
- The detection of erroneous simultaneous valve openings (i.e., BLT in manual mode) which can cause excess temperatures in the valve actuation unit or even material hanging in the hopper due to gas backflow from the blast furnace.
- The validation of the material gate operations (actual vs. setpoint, angle vs. flowrate) since the decrease in the opening angle during similar flowrates can indicate wear of the lower material gate.
- The verification of the correct pressurization and depressurization of the hoppers.
- The monitoring of all relevant chute transmission gearbox (CTG) data (temperatures, current, power, vibration, positioning of chute, cooling water flowrates, etc.) and the idle rotation current to validate the mechanical state. This also includes the monitoring and prediction of the main rotation bearing condition using vibration analysis, temperature and rotation current as well as calculations for the cooling water consumption, e.g., by enumerating water makeup cycles, and for the emergency cooling power.

RulesXpert makes it possible to capture and digitize the intricacies of human expertise. It is an integral part of condition monitoring which allows combining expert knowledge with data-driven insights. Additional rule logics can be integrated either by the equipment supplier or by the operator itself and allow the system to grow over time. This system acts as a knowledge base for process and maintenance engineers and contributes to the evolution of equipment and process monitoring.

Conclusions and Summary

The industrial sector needs to reduce the cost of operations, synchronize inventory management and efficiently organize personnel and equipment.[2] Data provides insight on the equipment behavior in order to avoid inappropriate use and to identify required maintenance actions based on the insights obtained.

In order to extract valuable knowledge for maintenance optimizations, a technology kit for engineers has been developed by Paul Wurth. It allows empirical knowledge that has been acquired over decades to be digitized and shared. Process and maintenance knowledge can be captured, stored and shared in order to create new powerful services and solutions for equipment and plants. The tool kit includes a module to aggregate and store data from production facilities, the module RulesXpert as the core environment for user-specific and knowledge-based rule development, the module AIXpert to train machine-learning models that can be integrated into the rules, and the module BIXpert to build web-based dashboards to visualize and share the results.

Based on Paul Wurth's experience as an OEM in the field of blast furnace charging systems, a wide set of solutions have been developed to continuously increase availability and ensure optimal performance and maintenance of ironmaking technologies. The paper has given a small, exemplary insight into the condition and performance monitoring of tapping machines and the Bell Less Top Charging System.

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