Digital Solutions for Modern and Efficient Ironmaking

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

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Since the beginning of industrialization, technological leaps have led to paradigm shifts, which today are known as industrial revolutions.[1] Nowadays, the emergence and prevalence of new information and communication technologies (ICT) are heralding a new digital age, known as the fourth industrial revolution — in short, Industry 4.0.[2] Such technologies will find their way to and will have a substantial influence on all industrial sectors. It's the transformation of today's factories into smart factories. These technologies are intended to overcome current challenges on the way to an efficient, resource-saving production in order to meet the continuously growing worldwide demand by simultaneously ensuring a sustainable evolvement of human existence in its social, environmental and economic dimensions.[3,4]

The integration and purposeful use of ICT will find their way into the ironmaking industry. Digital solutions will take over a crucial part of a modern, efficient iron production process and thus also offer great potentials. Most modern blast furnaces are already connected to state-of-the-art instrumentation and ubiquitous automation technologies, collecting and storing live and historical signal data from multiple sensors.[5] They are the prerequisite to applying digital solutions, as data is the raw material of the information age that puts new services such as process parameter predictions or predictive maintenance into practice. However, if no relevant data is available, new technologies such as connected sensors or data acquisition boxes can be integrated to easily gather and provide relevant data for almost every specific use case.

This paper gives insights into the integration and implementation of digital solutions in an ironmaking plant in Germany. This paper will first provide an overview on requirements and enabling technologies to realize corresponding use cases and to purposefully use embedded services. This is followed by applications and exemplary use cases, such as:

- Condition monitoring and smart maintenance approaches for casthouse machines and the slag granulation.
- The use of so-called smart sensors to monitor wear of staves in the blast furnace.
- Process optimizations and process predictions enabled by expert systems and the use of machine learning.
- A digital twin approach of the blast furnace itself in order to merge any existing data sets.

Requirements and Enabling Technologies

Common and Functional Requirements

— In order to ensure a seamless integration of digital solutions that are in line with a long-term digitization strategy, general requirements have jointly been identified by Paul Wurth S.A. as system integrator and ROGESA Roheisengesellschaft Saar mbH as end user. This enables an integration of individual solutions and services in suitable migration steps while ensuring that all scenarios build on each other and thus are part of a big picture. A distinction was made between common and functional requirements.

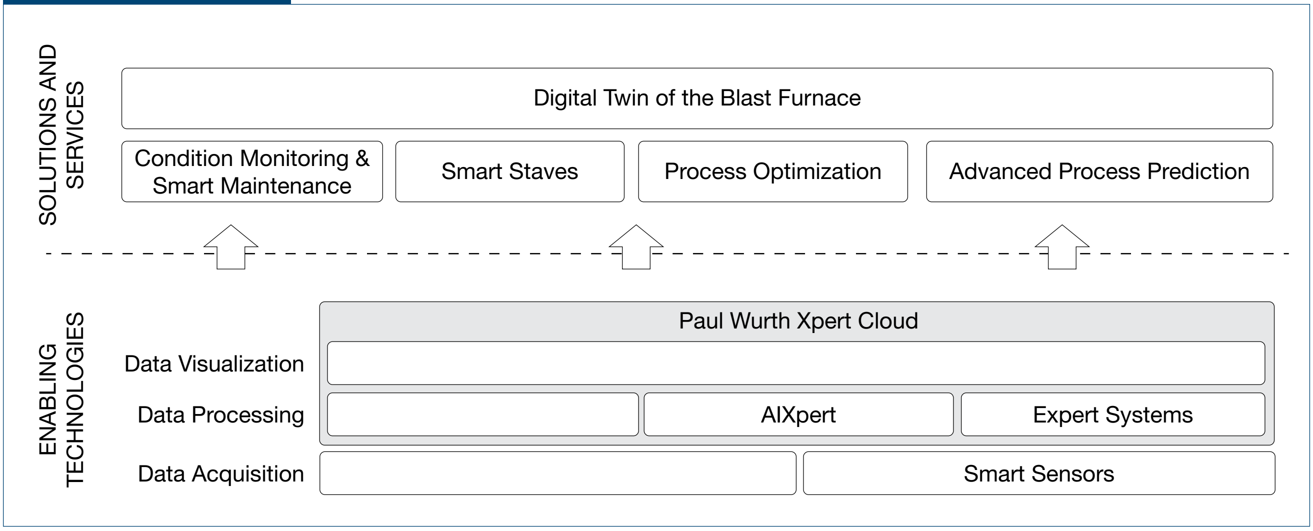
From a common perspective, the same basic technologies should initially be used for all overall scenarios and use cases. This guarantees a high degree of extensibility, meaning that new services to be added afterwards could build on technologies already in use in order to integrate them without major adaptations. Following the concept of modularity, this also implies the definition and use of pre-defined, standardized M2M interfaces between all technologies used. It should be possible to use them independently of each other while the combination of several basic technologies, depending on application, should also be feasible without time-consuming pre-configurations. It will lead to a high degree of scalability. Contrary to a monolithic approach, integrated solutions and services should be able to be adapted or extended to new requirements as it is a common circumstance of Industry 4.0. In addition, acceptance by industrial workers and plant operators who will work proactively with all technologies and services is of great importance. A holistic approach integrating digital solutions therefore implies that this includes, in particular, their needs. Interaction should be task- and user-oriented as well as target-oriented and intuitive.[6] Finally, from a common perspective, a secure exchange of confidential and sensitive information must be guaranteed by appropriate authentication and legitimation mechanisms.

From a functional point of view, the data aggregation should initially be independent of all vendor-specific communication protocols. Acquired data should be furthermore hierarchically classified, structured and consistently stored according to the end user's process or equipment structure. Using it as a basis, process engineers should be able to intuitively set up rule calculations (so-called white-box calculations) without any support of another programmer, e.g., to calculate application-specific key performance indicators (KPIs) or to trigger customized actions, warnings and alarms. In doing so, calculations should be applicable, on the one hand, to real-time data during ongoing production as well as, on the other hand, to historical data sets. The latter is intended to help to extract knowledge from already existing data sets, e.g., to execute rules for an event where a failure occurred. Scaling them across machines and plants should be possible. Process engineers should also be given the opportunity to actively and intuitively use machine learning methods. This implies the combination of white-box calculations mentioned above with data-driven approaches. The latter are also known as black-box models since they are containing logic that has not been defined on the basis of formulas. Decisions are made by trained algorithms whose logic is not always easy to understand. However, the process engineer should still keep the decision-making power. Finally, far-reaching access to all results with adjustable insight should be facilitated via a platform-independent front end. Results should be integrated and merged across all solutions and applications. A bi-directional communication between system and user should additionally enhance capturing and processing blue-collar worker feedback. All these requirements are fulfilled by the following implementations, which enable a step-by-step integration of various digital solutions by following an elaborated digitization strategy.

Key Technologies — Based on the requirements from the previous section, a brief overview on key technologies is given. They reflect the common layers of a three-tier architecture that are functionally separated: the data acquisition and management followed by the data processing and the data visualization. Key technologies used for the implementation of digital solutions (Fig. 1) can be summarized as follows:

- Paul Wurth XpertCloud: The IT infrastructure and data backbone — a platform to provide software as a service developed by Paul Wurth for using, creating new or extending existing applications in a secure cloud computing environment. It offers necessary storage and computing power and is available on demand without direct active management by the end user. The Paul Wurth Acquisition Box is used for gathering data out of the production. According to the requirements, it acquires data out of existing databases, programmable logic controllers (PLCs) or human-machine interfaces (HMIs) — independently of its format and of the communication protocol that has to be used. It is being semantically described, classified and persistently stored — either in a time-series database specifically designed for subsequent analyses or within relational databases, both to provide them to higher-level tools and applications.
- Smart Sensors: Key technologies within the future factory environment. Comprising sensor technologies with local processing intelligence, they are able to communicate in an Internet of Things (IoT) in order to interact autonomously with other field devices, machines and services through open networks.[7] This allows an easy integration, adaptation or replacement. Smart sensors are developed for specific applications and can be integrated into the existing infrastructure.
- RulesXpert: The rule editor is a basic service for the end user running on the Paul Wurth XpertCloud. Users have the possibility to access raw signals out of the time-series database in order to carry out white-box calculations. Once a rule has been defined, the user can either execute it on historical data stored within the

Figure 1



Key technologies enabling digital services.

database or publish the rule to execute it cyclically or event-driven during running production. As soon as a new rule has been defined, the former approach allows extracting immediately knowledge out of historical data sets.

- AIXpert: A complementary cloud solution within the Paul Wurth XpertCloud for advanced data analysis using machine learning. Following the requirements, process engineers and operators can use AIXpert to intuitively train artificial intelligence models. Afterwards, they can be integrated via drag-and-drop into RulesXpert. Running as a black-box they complement the former white-box approach.
- Data Visualization: By using a web interface, process engineers and plant operators are able to query, visualize and understand raw data, calculated values or extracted results platform-independently. This includes numerous functions for displaying data, both historical and real-time. All information can be merged into application-specific dashboards.

Digital Solutions and Services

As part of the collaboration between ROGESA and Paul Wurth, a wide range of topics has been or is currently being jointly developed and implemented. They will be discussed more in detail within the following section.

Condition Monitoring and Smart Maintenance — Looking at the life cycle of assets, they do not usually suddenly fail or stop working. More precisely, they will break down gradually, over a period of weeks, months or years. During that time, components will output numerous invisible warning signals (e.g., slight changes in vibration, in functional behavior or in general operation conditions). If these become perceptible for humans, it is usually too late and the wear is already advanced. In the worst case, repairs must be carried out when equipment has already broken down (reactive maintenance). It is a far more costly strategy due to unexpected stoppages and damaged machinery, especially as the unpredictable nature implies that manpower and spare parts may not be immediately in place. Ideally, this approach should only be applied on parts that are easy to replace and are less expensive. In order to avoid these risks, maintenance is also often carried out proactively in order to prevent its breakdown by periodically planned inspections and tasks[8] (preventive maintenance). However, the decision of whether an asset will enter the wear phase has traditionally relied on general estimates and averages rather than on actual statistics on its condition. Scaled to the entire production, this also leads to a costly maintenance approach as components are replaced even though they still work perfectly.

Enabled by advances in sensor and communication technologies as well as machine learning methods that are part of the IIoT,[9,10] data-based and data-driven strategies embody new innovative approaches in realizing a more economical and future-oriented maintenance. Data can easily provide insight on the equipment behavior in order to avoid inappropriate use and, furthermore, to identify required maintenance actions based on the insight obtained (known as condition monitoring). Afterwards, present conditions of machines or plants can be continuously compared to a historical baseline or classified to defined thresholds, well-known anomalies and patterns to improve maintenance (known as condition-based and predictive maintenance, or in general so-called smart maintenance).

Potential root causes of machine or plant failures can be determined and countermeasures can be taken in a timely manner before problems occur. The equipment lifetime can thus be extended and determined in the long term in order to carry out maintenance work at the most cost-efficient time. Ideally, smart maintenance allows the maintenance frequency to be as low as possible and still prevent unplanned reactive maintenance, without incurring costs associated with doing too much preventive maintenance.[11] It results in several cost savings, e.g., minimizing the time spent unnecessarily maintaining and inspecting equipment, lowering the risks of unplanned downtime, reducing the production hours lost through preventive and reactive maintenance approaches, or minimizing the cost of spare parts and supplies.

The condition monitoring and smart maintenance approach is being applied to the casthouse machines and slag granulation system. In order to gather all relevant signal data at the control level, the Paul Wurth Acquisition Box has been installed and has been given access to more than 200 raw signals each for both use cases. Signals can be either directly accessed via the graphical user interface or can be used for pre-calculations in RulesXpert. Following the new maintenance approach, the tool is actively used to both calculate general KPIs and runtime parameters as well as to detect behavioral changes and trigger appropriate maintenance in a timely manner.

Slag Granulation System: In close cooperation with the experts from the Iron Business Unit for Process and Technology, the following two main objectives are pursued for the slag granulation:

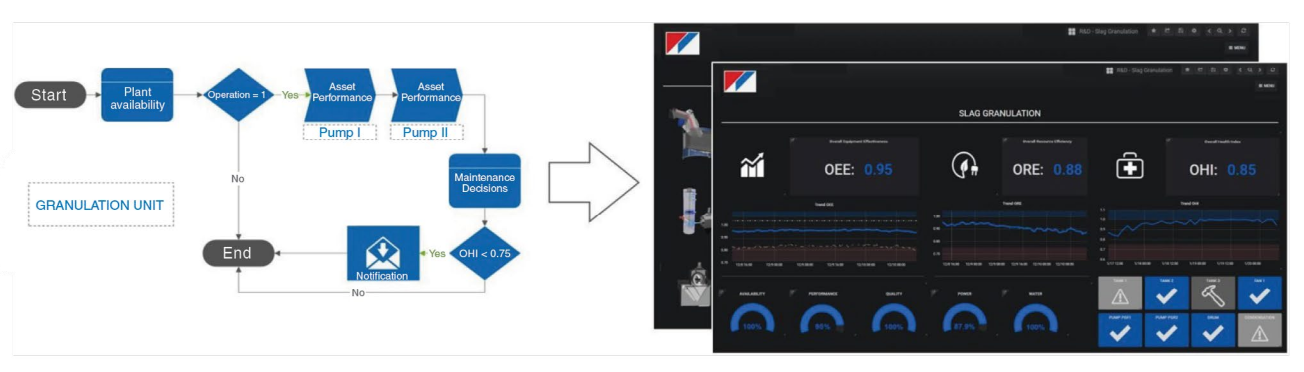
- Triggering the already existing preventive maintenance tasks based on its real runtime or based on the slag quantities that have been granulated. This should avoid using predefined time intervals that traditionally rely on general estimates and averages rather than on actual statistics. If the equipment is not operating for a few days, preventive maintenance can be reduced and carried out with a delay.
- Detecting behavioral changes of selected parts by comparing their condition to a historical baseline or classifying it according to defined thresholds, well-known anomalies and patterns.

In accordance with the objectives, the first rule set for the slag granulation system covers the fundamental aspects of general KPIs, known as overall equipment effectiveness (OEE) and overall resource efficiency (ORE). Insight is being given, e.g., into the following questions:

- How long is the plant generally in operation, especially between granulations?
- How long is the plant out of operation, and are there unscheduled downtimes?
- What would be optimal operating time and costs compared to its current operation?
- How much slag on average was granulated within its operating time?

Rules implemented were initially executed on all historical data sets to immediately gain knowledge out of past data before they were published to provide insight on live data during ongoing operation. Following the second objective, a third overall KPI has been established representing the equipment's physical condition. The so-called overall health index (OHI) reflects any deviations that are being monitored by further rules detecting behavioral changes.

Figure 2



Maintenance rules within RulesXpert based on asset performances.

This includes pressure or flowrate drops/increases in case of wear/contamination of nozzle plates or irregularities in drying slag in case of contamination and wear on the drum. Fig. 2 provides an exemplary insight on a rule defined within RulesXpert to trigger mail notifications or maintenance instructions based on the asset performances during plant operation. Furthermore, it illustrates corresponding dashboards that can be easily generated based on all results.

Casthouse Machines: The following use case was developed in close cooperation with TMT's experts. The main objective by applying the smart maintenance approach on casthouse machines is to enhance transparency of the tapping process in order to advise and improve the process itself. A second step consists of enlarging knowledge for operational and maintenance benchmarking, e.g., between different equipment setpoints, tapholes or shifts. In practice and in accordance with the objectives, the first rule set includes, among other things:

- Monitoring the operating time of main components (e.g., hammer unit, cylinder) to draw conclusions on the equipment service life.
- Observation of various process values (e.g., taphole length, used clay volume, time between two tapping operations, air inclusions in the taphole channel).
- Optimization of the drilling and plugging processes (e.g., effective use of the hammer unit, maximum duration of the drilling process/operational reliability of the blast furnace, consumables used).
- Monitoring of machine functionalities (e.g., long-term changes of parameters such as slewing pressures).
- Machine maintenance benchmarking of several tapholes at one furnace (in the long term also of several furnaces).

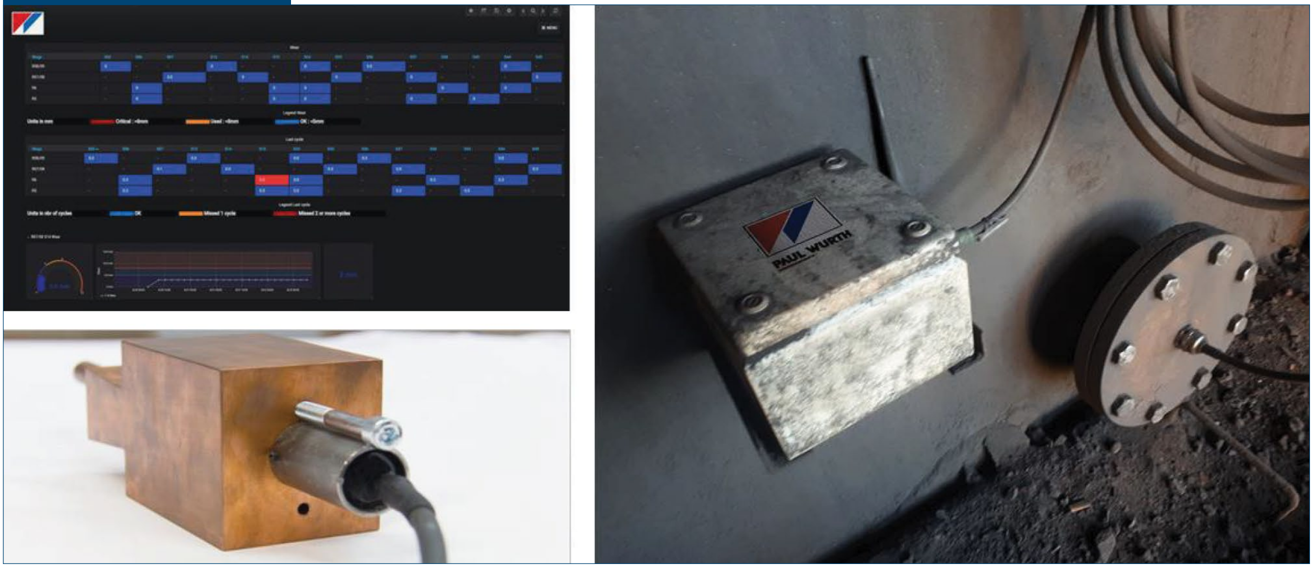
Information is provided to ROGESA on various levels of abstraction. Following the approach on the slag granulation system, all calculations are therefore also consolidated in the three overarching KPIs: OEE, ORE and OHI. For visualization, the same web user interface is used.

Smart Sensors for Wear Condition Monitoring of Copper Staves

Smart Sensors for Wear Condition Monitoring of Copper Staves — Copper staves can be seen as one of the best wall-cooling elements for high-heat loads of blast furnaces. The well-proven approach guarantees that blast furnaces can resist high temperatures and are readily available in order to achieve a high level of productivity. However, copper staves could also be subject to wear and degradation due to burden friction. This wear is difficult to predict and can lead to critical situations where unexpected stave replacement in very short term is needed.

All currently available methods to assess this wear, such as measurements using ultrasonic technology or visual inspections, can only be applied during blast furnace shutdowns so that wear might be detected too late. The prevalence of ICT in this case opens the door to develop new probes that are not affected by measurement distortion and which regularly transmit data on wear conditions of staves. In concrete terms, a patented smart sensor has been developed

Figure 3



Smart Stave sensor and its installation.

representing an innovative approach to pave the way for a continuous, cost-effective and simple wear condition monitoring of staves.

The solution has been developed in close cooperation with experts from the general engineering department. Designed as a functionally isolated unit, the Smart Sensor is mounted in a drilled hole on the stave (Fig. 3), which can also easily be drilled during a blast furnace shutdown in case of retrofitting. Made of copper, the sensor wears out together with the stave and thus measures the residual thickness. Energy consumption is kept at a strict minimum. The measuring precision is up to 0.5 mm. A measurement frequency of one measurement per day is sufficient for long-term monitoring. In order to avoid significant cabling costs, all data are being transmitted via wireless network to the Paul Wurth XpertCloud. Data measured by the sensor and analyzed by a single-board computer is encrypted and securely transferred to the central database. Merged with all other measurements of all sensors installed, they can be visualized in the web interface. The dashboard provides a common overview of the staves condition. Data can be combined with operating temperatures or charging profiles simulated by charging models to foresee degradation of staves and avoid their early destruction due to a bad furnace operation.

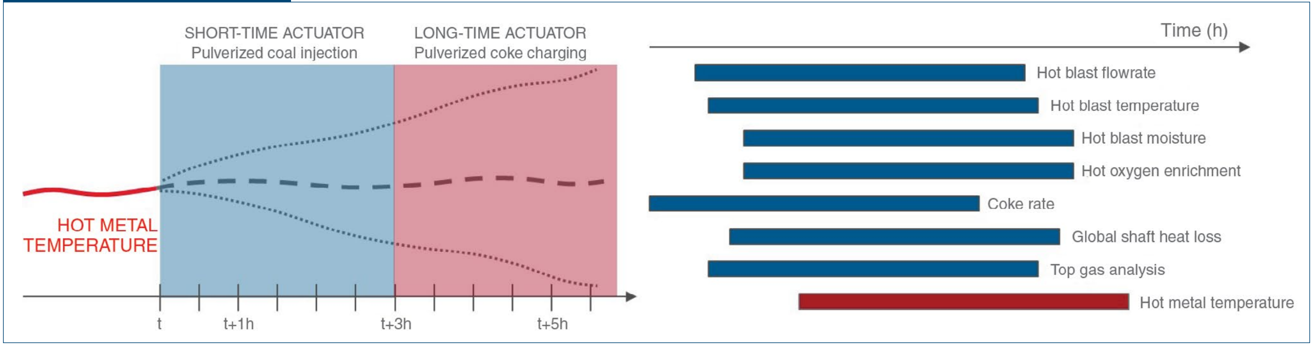
Advanced Process Predictions — Nowadays, the blast furnace reflects a complex control system in which various parameters are highly influencing the hot metal production process and its quality.[12] The hot metal temperature especially can be seen as one key quality indicator that is mainly influenced by actively controlling two sets of inputs to the furnace — the coke and ore inputs from the top of the furnace as well as the pulverized coal and air blast at the lower levels. Nevertheless, the current process characteristic and conditions do not make it easy to predict this key indicator.

Due to the operating conditions and very high temperature inside the blast furnace of more than 1,000°C, the temperature cannot be measured continuously using fixed installed sensors. Manual measurements are irregularly performed only a few times per cast at the outlet of the furnace, reflecting a mean-reverting, non-uniform time series centered on a locally fixed temperature target with significantly high correlation to its past evolution due to operator control.[5] Furthermore, changes in process conditions have a time-delayed effect on the hot metal temperature. The coke rate influences, for example, the hot metal temperature after 6–8 hours, whereas the effect of changes on the injected fuels takes 3–4 hours due to the proximity of the injection to the hot metal bath located at the bottom of the blast furnace.[13] It is schematically depicted in Fig. 4.

Triggered by the advance in machine learning, a data-driven approach facilitates the process of modelling complex systems, overcoming current restrictions of pure formula-based calculations. ROGESA blast furnaces are already equipped with state-of-the-art instrumentation, various sensor technologies providing a large set of raw data, as well as level 2 software with proven white-box control systems. As a part of the ongoing digitalization project, the hot metal temperature forecasting has been modeled as a supervised learning problem that combines an innovative black-box approach by using artificial intelligence (AI) with existing white-box models, representing long-standing experience in chemical and thermodynamical modeling of blast furnaces.

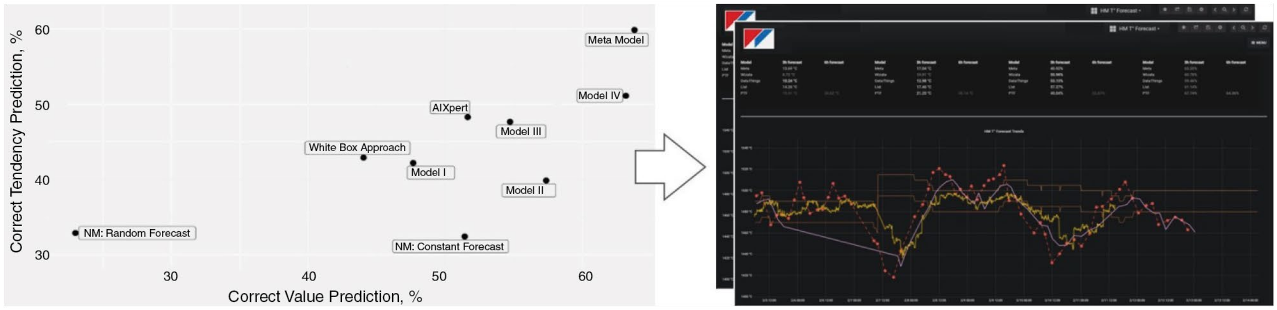
Based on more than 80 process variables available over a period of one year, several base models focused on different AI algorithms have been trained. Base models were developed in cooperation with cooperating research institutes. Furthermore, AIXpert has been used to actively involve process engineers to independently train corresponding AI models. Predictions are made in a time horizon of 3–6 hours.

Figure 4



Time-delayed influence of parameters on hot metal temperature.

Figure 5



Prediction accuracy of all models and visualization in the web interface.

An overall meta model learns the characteristics and compensates the biases of all data-driven base models and existing white-box calculations. This means that it should not replace existing approaches but actively support and combine them by innovative data-driven concepts. As a final step in order to apply them on live data, all models have been integrated as black boxes into RulesXpert. A purely data-driven approach has natural disadvantages such as difficulties in explaining models in order to justify and evaluate the accuracy of a prediction. These disadvantages are also overcome by using RulesXpert. Models are only giving predictions for known operation conditions and, thus, predictions are automatically evaluated afterwards. The meta model has been evaluated on a period of 6 months while a performance increase of more than 42% compared to state-of-the-art white-box approaches and 13% compared to the best black-box base model is reached (Fig. 5).[3]

Process Optimization of the Blast Furnace by Expert Systems — The efficient operation of modern ironmaking requires a high degree of automation in conjunction with computerized monitoring and control systems. Next to the necessary required level 1 automation, the customer's ironmaking process is also precisely monitored and optimized by process control systems BFXpert and SinterXpert. The former includes general process models for data analysis and process optimization and supports plant operators in optimizing the stability and costs of hot metal production, while being assisted by the knowledge-based system.[14] Treatment of process data further assists in reporting performance indicators and production figures.

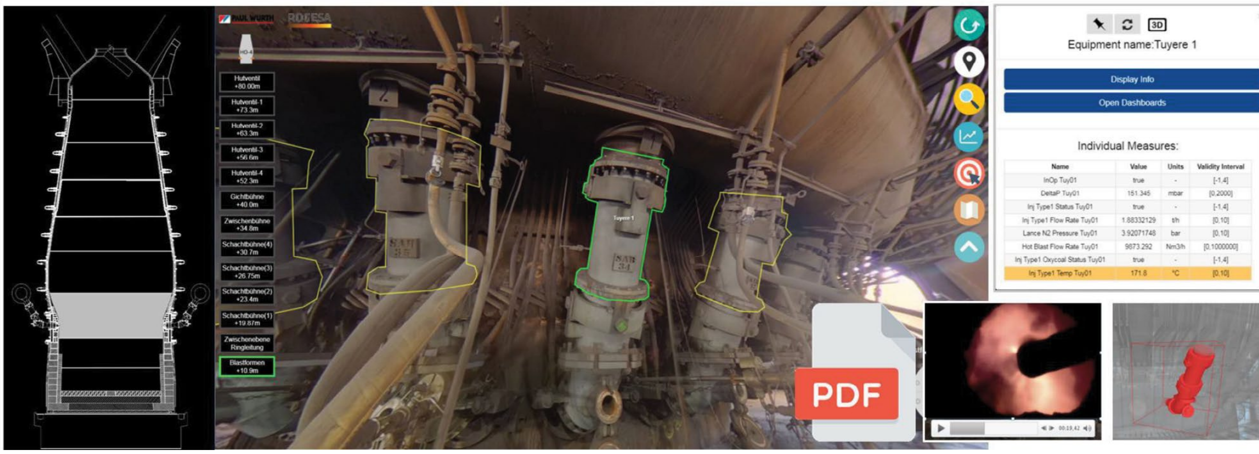
SinterXpert offers the same functionalities for sintering such as an integrated mix calculation model, an on-line mass balance or a burn-through point monitoring model.[15] SinterXpert is already being integrated as a "software as a service" (SaaS) solution. The software is licensed on a subscription basis and centrally hosted within the Paul Wurth XpertCloud. SaaS can be seen as an "on-demand software" approach and will become a common delivery model for many business applications.

Digital Twin of the Blast Furnace — Once the physical and digital environments merge, digital twins are born. They arise at the beginning of production development and grow over the entire planning process to the start of production. Highest potential can be expected within the ongoing production. Various data sets from the early engineering steps such as geometry models (M-CAD) and electrical plans (E-CAD) can be structurally combined and jointly provided with equipment's live data and behavior.[16] Doing so, the digital twin is increasingly turning into a so-called digital shadow. Accordingly, they are facing today's challenges of insufficient data consistency and lack of model data management due to the growing heterogeneity of digital solutions and services.[17] The overall objective of the digital shadow approach for the blast furnace was therefore to provide process engineers and plant operators easy access to relevant data and knowledge derived from different services and solutions.

As a basis for further visualization, a detailed panorama photo of the real blast furnace was taken. Users have the possibility to navigate through different platforms and to all accessible plant levels of the blast furnace in order to explore every corner and equipment from at least one detailed perspective (Fig. 6). If available, this visualization can also be replaced or supplemented by the detailed geometric model out of the planning phase. In the second step, relevant information was linked with the corresponding equipment of the blast furnace. This includes relevant engineering data such as drawings or geometric models, on the one hand, as well as all live data of components on the other, which can be accessed by an automatically generated dashboard.

Fig. 6 depicts exemplary data sets of the tuyeres. All available data sources, whether from the planning

Figure 6



Digital twin approach of the blast furnace.

phase or information and knowledge from integrated systems and digitization solutions, are merged within the digital shadow. It can be gradually enriched. Besides data already mentioned earlier, the user has for example also the possibility to view corresponding live videos. Close inspection of the tuyeres is particularly important as critical incidents such as a blockage or burning of the injection lance can happen at any time. To increase operation safety, a camera-based monitoring system is installed.[18]

All information can be accessed either using the traditional web browser or by using new interaction technologies such as smart glasses, for example, to future support maintenance by innovative means. Views can be saved and markers can be created in order to share this information with operative colleagues. The use of new interaction technologies makes it possible either to supplement objects from the real world with computer-generated perceptual information (augmented reality) or to completely replace the user's real environment with the simulated environment (virtual reality).

Conclusions and Outlook

The ironmaking industry will increasingly benefit from the advances in ICT and computer science. This paper showed a selection of integrated solutions and realized application scenarios at ROGESA. For their implementation and integration, common and functional requirements have been identified and fulfilled by the use of Paul Wurth key technologies. Further applications and use cases are being jointly developed. With regard to smart maintenance, for example, machine learning methods are actively used in the future to further improve and to predict upcoming failures or behavioral changes. Initially, general KPIs and first maintenance rules, following the white-box approach, were developed. By using AIXpert, process engineers and system operators are also able to follow the more advanced black-box approach to easily find anomalies, patterns and faulty behavior of their equipment. Trained AI models for the hot metal temperature prediction are currently being tested, evaluated and optimized in real production.

References

1. H. Lasi, P. Fettke, H.G. Kemper, T. Feld and M. Hoffmann, "Industry 4.0," Business & Information Systems Engineering, *International Journal of Information Systems,* 2014, pp. 239–242.
2. H. Kagermann, W. Wahlster and J. Helbig, "Securing the Future of German Manufacturing Industry: Recommendations for Implementing the Strategic Initiative Industrie 4.0," German Academy of Science and Engineering, Munich, Germany, 2013.
3. G. Seliger, H. Kohl and J. Mallon, "Opportunities of Sustainable Manufacturing in Industry 4.0," *13th Global Conference on Sustainable Manufacturing — Decoupling Growth From Resource Use,* 2016.
4. S. Weyer, M. Schmitt, M. Ohmer and D. Gorecky, "Towards Industry 4.0 - Standardization as the Crucial Challenge for Highly Modular, Multi-Vendor Production Systems," *IFAC Symposium on Information Control in Manufacturing,* Ottawa, Canada, 2015.
5. U. Iffat, S. Bhatia, A. Tantar, J. Sanz, C. Schockaert, A. Schmitz, F. Giroldini, Y. Reuter and F. Hansen, "New Digital Services for Manufacturing Industry Using Analytics: The Case of Blast Furnace Thermal Regulation," *IEEE 20th Conference on Business Informatics (CBI),* Vienna, Austria, 2018.
6. D. Zühlke, *User-Friendly Development of Human-Machine Systems,* (in German) Berlin, Springer, 2012.
7. M. Broy, H. Kargermann and R. Achatz, "Agenda Cyber Physical Systems: Outlines of a New Research Domain," *acatech,* Berlin, 2010.
8. L. Pintelon and A. Parodi-Herz, "Maintenance: An Evolutionary Perspective," *Complex System Maintenance Handbook,* London, Springer, 2008, pp. 21–48.

9. A-R. Sadeghi, C. Wachsmann and M. Waidner, "Security and Privacy Challenges in Industrial Internet of Things," *IEEE Design Automation Conference (DAC),* Las Vegas, Nev., USA, 2015.
10. R. Chitkara and R. Mesirow, "The Industrial Internet of Things: Why It Demands Not Only New Technology — But Also a New Operational Blueprint for Your Business," PricewaterhouseCoopers (pwc), London, 2018.
11. K. Richter and J. Walther, *Supply Chain Integration Challenges in Commercial Aerospace: A Comprehensive Perspective on the Aviation Value Chain,* Heidelberg, Springer, 2019.
12. H. Colpaert, *Metallography of Steels: Interpretation of Structure and the Effects of Processing,* ASM International, 2018.
13. Y. Reuter, P. Bermes, C. Schockaert, R. Lin and J-P. Simoes, "Blast Furnace Process Optimization With Data-Driven Models," *Aachener Stahlkolloquium,* Aachen, Germany, 2018.
14. J-P. Simoes, P. Tockert, L. Hausemer, C. Bodeving and P. Bermes, "BF Process Technology Enhanced by Charging Control, Process Monitoring and Mathematic Models," *19th IAS Steel Conference,* Rosario, Argentina, 2013.
15. "Furnace Automation and Supervisory Systems," Paul Wurth S.A., http://www.paulwurth.com/Our-Activities/Ironmaking/Furnace-Automation-Supervisory-Systems, accessed 10 February 2019.
16. E. Negri, L. Fumagalli and M. Macchi, "A Review of the Roles of Digital Twin in CPS-Based Production Systems," *27th International Conference on Flexible Automation and Intelligent Manufacturing, FAIM2017,* Modena, Italy, 2017.
17. S. Weyer, "Methodology for Information Technology Integration of Cyber-Physical Production Systems Within the Digital Factory," (in German) Technical University of Kaiserslautern, 2018.
18. H. Zewe, A. Daelman, Y. Reuter, P. Van Dorpe and J-P. Simoes, "Results of Using a Tuyere Phenomena Detection System," *Stahl und Eisen,* Vol. 134, 2014, pp. 39–47. ✦

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Did You Know?

ArcelorMittal Cleveland Employees Recognized for Low-Cost Energy-Saving Projects Through "Power of 1"

For the past several years, ArcelorMittal Cleveland's energy team has hosted the "Power of 1" energy innovation contest, encouraging employees to propose no- and low-cost ideas to conserve energy at the plant. The winning ideas from three employee teams will save hundreds of thousands of dollars in energy costs.

"One of the most important things we can do is get our people focused on energy efficiency. Our employees know our plant and systems best, and often they can easily identify opportunities to make our facility more efficient. The ideas proposed in this year's contest were simple but impactful, showcasing the power of one person or team to help us reach our energy goals," explained Rishabh Bahel, manager – utilities and energy conservation.

The top three ideas included:

- A plan to automatically control one of two hydraulic pump motors at the No. 1 Steel Producing caster will turn it off when not needed for the operation. Historically, both pumps were operating 24 hours a day, even when one would be sufficient. This project can be implemented in-house by reprogramming a programmable logic controller, with no investment cost. Project team members: Luis Rodriguez, Gary Czapor and Joel Rakocy.
- Another team at No. 1 Steel Producing's ladle metallurgy furnace is implementing a new procedure to save compressed air during and between degassing sequences. Team members noticed that large volumes of compressed air were being wasted in this process and devised a simple pushbutton solution to turn off compressed air when it's not being used. They estimate this change will reduce the air consumption related to this job by 90%. Project team members: Joseph DiPinto, Mike Gole, and Joel Rakocy.
- Focusing on natural gas, a team of reliability engineers from the maintenance, engineering and utilities division used a special infrared camera to detect leaks. Within a short two-hour walk-through of two on-site facilities, the camera helped identify five significant natural gas leaks. Repairing these leaks is projected to save more than US$200,000. Project team members: Scott Hitchings, William A. Rinehart and Rishabh Bahel.

"Developing an energy-efficient system doesn't just impact the company, it also benefits the world. Simply because something has been done a certain way for a long time doesn't mean it is the most energy- or cost-efficient way," said Joel Rakocy, electrical project engineer and Power of 1 winner.

"My teams and I are always looking for ways to improve a process to make it more efficient. I encourage others to look at the systems they use regularly and work with their teams to discuss pain points. A little conversation may result in a large improvement to reduce energy consumption, reduce costs, decrease maintenance and even improve day-to-day operational time."

Submitted ideas were judged by Helder Silva, ArcelorMittal Global chief technology officer.

Through the U.S. Department of Energy's Better Plants program, ArcelorMittal USA has committed to significantly reducing its energy intensity. The Power of 1 projects meaningfully contribute to that goal.