DIGITAL SOLUTIONS FOR MODERN AND EFFICIENT IRONMAKING*

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Abstract

Digitalization of our industry is bringing new opportunities to further optimize operation including production and maintenance. One of the biggest drivers of this digital wave is the artificial intelligence based on big data in combination with process knowledge and IoT technologies. This paper describes the approach to and the status of implementation of modern digital solutions at Rogesa ironmaking plant. The Rogesa implementation includes L2 automation packages for sinter plant and blast furnace process optimization, deep learning with data-driven models. staves wear monitoring by smart sensors, production KPI monitoring via mobile dashboards, condition-based predictive and prescriptive maintenance for tapping equipment and the slag granulation plant as well as a digital twin of the blast furnace using virtual and augmented reality for the visualization of live data, alarms etc. on a 360° tour through of the plant.

Keywords: Industry 4.0, blast furnace, sinter plant, process optimization, energy and resources efficiency, wear monitoring, KPI dashboard, smart maintenance, predictive maintenance, digital twin, 360 tour, smart sensors

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1 INTRODUCTION

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 certainly find their way and will have a substantial influence on all industrial sectors. It's the transformation of today's factories into smart factories. They are attended 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 certainly 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 apply digital solutions – as data is the raw material of the information age in order to put new services such as for 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. The reader gets first an overview on overall 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 cast house 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

2 DEVELOPMENT

2.1 REQUIREMENTS AND ENABLING TECHNOLOGIES

2.1.1 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 predefined, 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-users' 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 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. 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 easily 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 so-called black-box and data-driven approaches. However, the process engineer should still keep the decision-making power. Finally, a far-reaching access to all results with adjustable insight should be facilitated via a platform-independent frontend. 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.

2.1.2 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 visualisation. Key technologies used for the implementation of digital solutions (Figure 1) can be summarized as follows:

- *Paul Wurth XpertCloud:* It represents 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, PLCs or 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:*** **They are 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, adaption 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 execute it either on historical data stored within the 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:* It is 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 AI 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 Visualisation:* By using a web interface, process engineers and plant operators are able to query, visualize and understand platform-independently raw data, calculated values or extracted results. This includes numerous functions for displaying data, both historical and real-time. All information can be merged into application-specific dashboards.

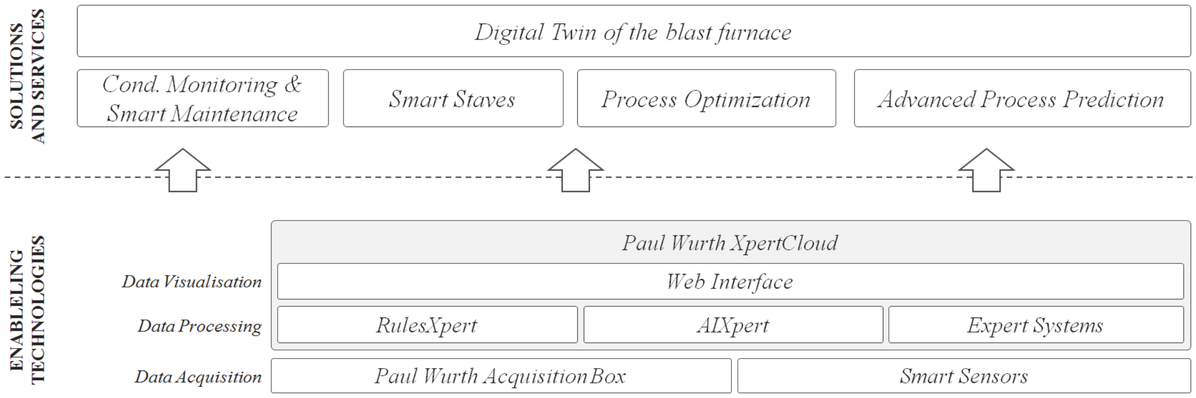

Figure 1: Key technologies enabling digital services

2.2 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 chapter.

2.2.1 Condition-Monitoring and Smart Maintenance

Looking at the life cycle of assets, they will usually not 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 of 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, in particular 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 less expensive. In order to avoid these risks, maintenance is also often carried out proactively in order to prevent its breakdown by periodically planed inspections and tasks [8] (*Preventive Maintenance*). However, the decision 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 the advance in sensor and communication technologies as well as machine learning methods that are part of the *Industrial Internet of Things (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 behaviour in order to avoid an 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 life time 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 cast house 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 both to calculate general KPIs and runtime parameters as well as to detect behavioural changes and trigger appropriate maintenance in a timely manner.

2.2.1.1. 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 pre-defined 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 behavioural 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 is covering 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 in average was granulated within its operating time?

Rules implemented were initially executed on all historical data sets to gain immediately knowledge out of past data before they were published to provide the 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 behavioural changes. This includes pressure or flow rate drops/increases in case of wear/contamination of nozzle plates or irregularities in drying slag in case of contamination and wear on the drum. Figure 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.

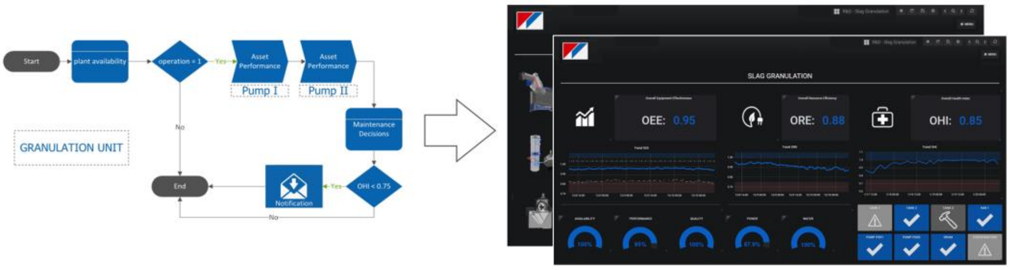

Figure 2: Maintenance rules within *RulesXpert* based on asset performances

2.2.1.2. Cast House Machines

The following use case is developed in close cooperation with TMT's experts. Main objective by applying the *Smart Maintenance* approach on cast house machines will be 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 set points, tap holes 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. tap hole length, used clay volume, time between 2 tapping operations, air inclusions in the tap hole 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 tap holes 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.

2.2.2 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 opens in this case 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 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 (Figure 3) which can also easily be drilled during a BF 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 analysed by a single-board computer is encrypted and securely transferred to the central data base. 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.

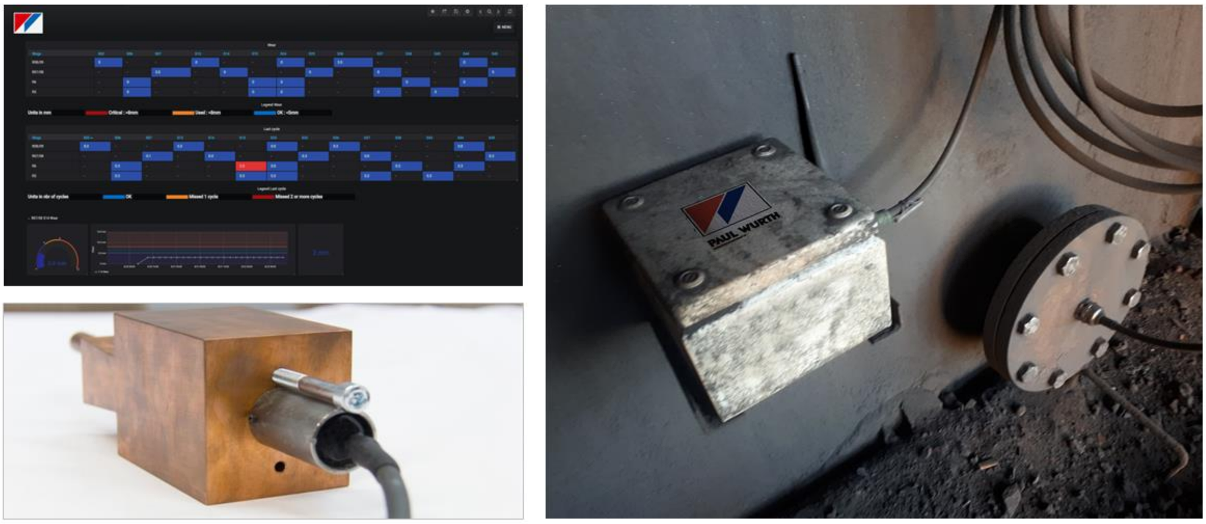

Figure 3: *Smart Stave* Sensor and its installation

2.2.3 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]. Especially the hot metal temperature 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 1000°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 centred 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 h 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 Figure 4.

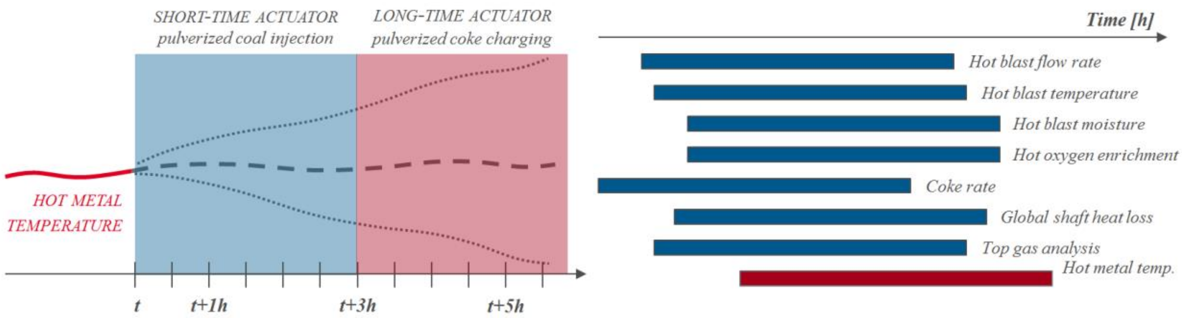

Figure 4: Time-delayed influence of parameters on hot metal temperature

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 digitalisation project, the hot metal temperature forecasting has been modelled as a supervised learning problem which combines an innovative black-box approach by using artificial intelligence with existing white-box models, representing long-standing experience in chemical and thermodynamical modelling of blast furnaces.

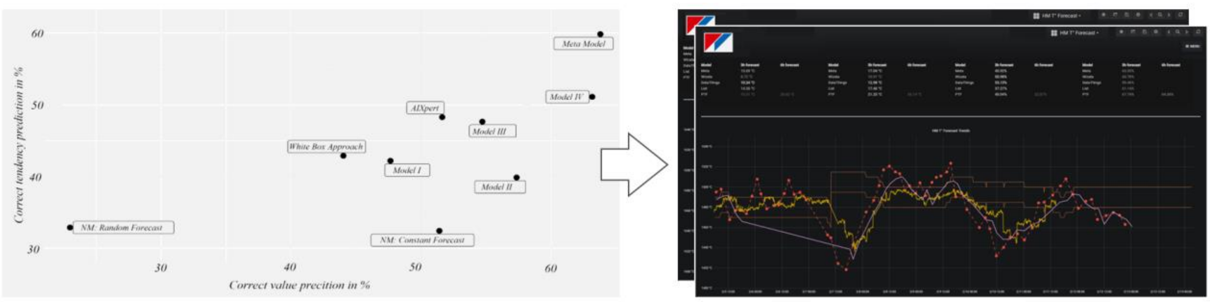

Figure 5: Prediction accuracy of all models and visualization in the web interface

Based on more than 80 process variables available over a period of 1 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.

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 naturally disadvantages such as difficulties to explain 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 (Figure 5) [3].

2.2.4 Process optimization of the blast furnace by expert systems

The efficient operation of modern ironmaking requires a high degree of automation in conjunction with computerised monitoring and control systems. Next to the necessarily required Level 1 automation, the costumer's ironmaking process is also precisely monitored and optimized by the advanced 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 online mass balance, or a burn-through point monitoring model. [15] As a major step towards *Industry 4.0*, *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.

2.2.5 Digital Twin of the Blast Furnace

Once the physical and digital environments are merging, *Digital Twins* are born. They arise at the beginning of a 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 behaviour [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]. 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 basis for further visualization, a detailed panorama photo of the real blast furnace was taken. User 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 (Figure 6). If available, this visualisation can also be replaced or supplemented by the detailed geometrical 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.

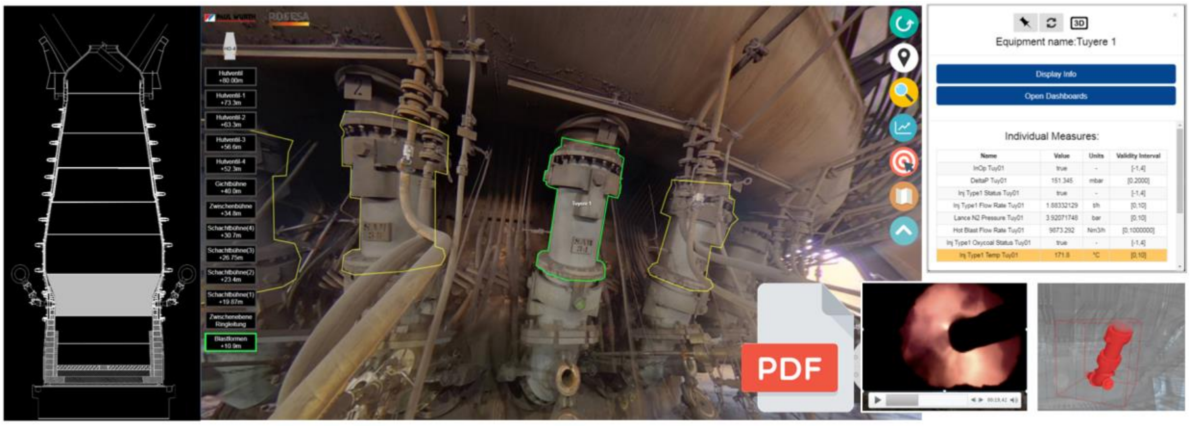

Figure 6: Digital Twin approach of the Blast Furnace

Figure 6 depicts exemplary data sets of the tuyeres. All available data sources, whether from the planning 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 above, 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 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 to 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 by the simulated environment above (*Virtual Reality*).

3 CONCLUSION

The ironmaking industry will increasingly benefit from the advance in ICT and computer science. The paper shows 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 purposeful 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 behavioural 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 behaviour of their equipment. Trained AI models for the hot metal temperature prediction are currently being tested, evaluated and optimized in real production.

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