11th ECCC

11th European Continuous Casting Conference

October 2024 | Philharmonie Essen Conference Center

# Ladle Slide Gate Health Monitoring for Steel Industry: Overcoming the Industrialization Challenges of Data-Driven Diagnostics in Steel Plants

Verena Schmidt[1], Adi Mehmedovic[2], Till Schöpe[3], Christoph Netsch[3], Fabio d'Isidoro[4]

[1]RHI Magnesita Switzerland AG, Switzerland. [2]RHI Magnesita GmbH, Austria.
[3]Alpamayo Intelligent Quality Solutions GmbH, Switzerland. [4]CSEM, Switzerland.

*verena.schmidt@rhimagnesita.com*

## ABSTRACT

The steel industry is undergoing a transformative phase with the advent of digitalization and automation technologies. A system was developed and implemented to track the condition of ladle slide gate refractories during operation. It aims at providing operators with timely insights on ladle slide gate conditions and guidance to support decision making at the ladle preparation area.

Digital twins of refractory components consolidate data of different sources and process steps along their lifecycle. We will give insights on how data driven, classical as well as machine learning based models, support slide gate refractory plate condition assessments. Then, we will provide an outlook on how such models can be used to estimate the remaining lifetime.

The framework and methodology presented in this paper aims to offer insights into overcoming the obstacles in the industrialization of data-driven solutions within the steel sector.

The architecture selected streamlines the implementation of data-driven tools in the steel industry, considering the stringent data sharing requirements and the heterogenous infrastructure.

Results will be presented demonstrating the application of the system to detect critical situations with the operation of ladle slide gate systems and support operators in decision making related to refractory components at the ladle preparation area.

Keywords: *Ladle slide gate, Condition Monitoring, Digitalization, Digital Twin, Data-Driven Solutions, Slide Gate Refractories*

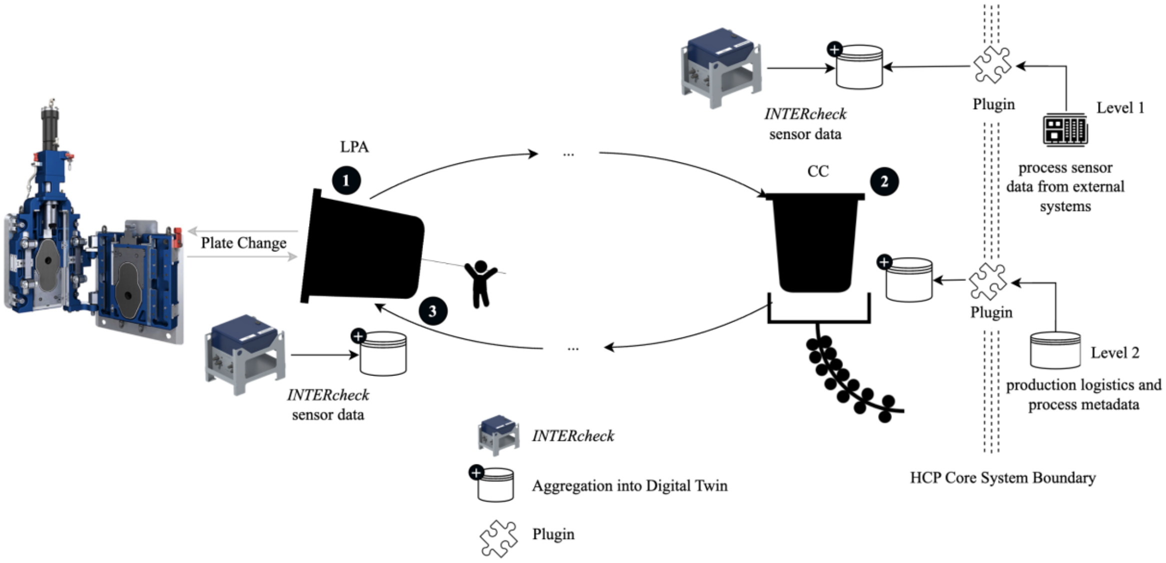


**Figure 1 Data defined by the Health Check Platform's information model is aggregated in each plate's digital twin as the plate circulates through relevant process steps of the steel casting process.**

## 1. INTRODUCTION

In recent years, the requirements for flow control systems have radically changed and technologies like robotic cells and digital tools are being adopted to perform these operations automatically on the caster [1]. On the other hand, at the ladle preparation areas, the processes still heavily rely on manual work and operator's experience to decide on the appropriate time to change the consumable refractory components. Operators are exposed to harsh environments in terms of handling of heavy loads, and working in areas with high temperatures, loud noises and dust.

In advance to the introduction of full automated, robotic operation at the lade preparation area, *RHI Magnesita* (RHIM) is developing a system to monitor the conditions of slide gate systems and refractories. Processes can be continuously improved by collecting within digital twins and analyzing data with algorithms. The introduction of digitization into decision-making also means that process knowledge remains available even when experienced employees retire. In addition, the digital system can learn by adapting its parameters to unforeseen events. Improved decision-making will lead to higher operational reliability, lower costs and reduced $CO_2$-emissions. Application of this solution will also contribute to faster know-how transfer and training of new personnel [2] [3].

### 1.1 Health Check Platform – a Digital Twin for Flow Control System Health Monitoring

Recently, the term digital twin has been used extensively both among researchers and practitioners to describe various concepts related to digital manufacturing. While literature presents numerous (inconsistent) definitions [4], likely due to the number of distinct use cases, that digital twins have been developed for. As formulated by [5] [6] for the purpose of health monitoring, we consider a digital twin of an asset to combine:

a) a process- and equipment-specific information model, that establishes semantic relationships between all data linked to the asset, particularly relationships between components, process steps, failure modes, and how process and sensor data is related to them,

b) sensor, process, and production data aggregated over the asset's lifecycle,

c) and an analytical framework, capable of transforming process and sensor data into relevant health data.

#### 1.1.1 Information Model & Plate Lifecycle Data Aggregation

To provide the necessary background for a discussion of the industrialization challenges, we present how the concept of a digital twin materializes in the *Health Check Platform* (HCP) developed by RHIM for the purpose of plate health monitoring and diagnostics. Based on an analysis conducted by experts with extensive experience in the steel industry, we outline an information model developed as an abstraction covering those process steps, that each plate experiences one or multiple times throughout its lifecycle, focusing uniquely on those process steps, critical to assess its condition (Figure 1). Notably, our approach does not introduce any additional procedures to the process and uniquely relies on available data and standard sensors – no specialized metrology equipment is required:

1) During slide gate maintenance activities and refractory installation processes at the ladle preparation area (LPA), *INTERcheck* (Figure 2), a data acquisition system, which can be retrofitted to the LPA's hydraulic actuators, logs data via its built-in sensors in response to slide gate opening and closing cycles as a reference of the plate's healthy state.

2) While the slide gate position is controlled to regulate the flow into the tundish throughout the casting process, data is logged from *INTERcheck*. Data from this critical process step is synchronized with sensor measurements from adjacent systems (*level 1 data*), such as the tundish level control (TLC). The corrosive properties of the melt, a plate comes in contact with, are known to have a major influence on several plate failure modes. Therefore, production logistics data (*level 2 data*), including information about the melt's chemical composition, originating steel mill's production management system is aggregated in the digital twin.

3) For the purpose of routine maintenance and inspection at the LPA, after each casting operation, a slide gate opening and closing cycle is executed following an identical sequence of hydraulic cylinder movements as in (1). Similarly, the data response measured by *INTERcheck* is stored. Additionally, the operators' decision, whether a plate is reused or discarded, is stored, alongside a code mapping to an identified mode of failure, if applicable (Table 1).

Depending on the size and complexity of the steel plant, multiple ladles are in circulation and multiple LPAs are used for the maintenance activities. To ensure, that the data originating from these systems is synchronized correctly, we rely on level 2 data. *Section 3* will provide further examples, why knowledge of the equipment that interacts with the plates must also be included in the information model via standardized asset descriptions, to ensure that data is interpreted and normalized correctly.

### 1.1.2 Analytical Framework

Under the premise that the HCP recommendation system should provide operators with the necessary information to make decisions regarding the reuse or replacement of refractory plates more confidently, an analysis was conducted with the participation of both operators and refractory experts. This analysis determined the following analytical requirements in terms of *virtual sensors,* which can be computed using the data described in *Section 1.1.1*:

- Casting time
- Steel erosion index (based on chemical composition of key elements like Ca, Mn, C)
- Force or work required to operate the slide gate
- Transfer time from caster to ladle preparation area, etc.

With respect to several health indicators, knowledge of their progression is considered particularly important for their interpretation.

Due to their ability to directly infer plate reusability, predictive models, were determined as additional decision support information and a necessary requirement for automation purposes. Due to the dynamic operations at a given site, where HCP is deployed, and the heterogeneity of environments between sites, the ability of predictive models to adjust based on human feedback was deemed a further critical requirement.

Our contribution intends to highlight the industrialization challenges, that are frequently experienced, when introducing such data-driven tools into production environments (*Section 2*), and provide practitioners with guidance, by discussing the fundamental design choices of the HCP, which address these challenges (*Section 3*). The implementation details of its analytical framework remain beyond the scope of this paper, which focuses on the industrialization challenges of the innovation. However, the reference implementation of one site, presented in *Section 4* briefly describes how both unsupervised and supervised machine learning algorithms were used to predict plate reusability using all lifecycle data and presents performance benchmarks from one site.

## 2. INDUSTRIALIZATION CHALLENGES

Unlike the research-focused stages of innovation projects in digital manufacturing, the industrialization stage presents additional challenges. These challenges include the need for data integration with heterogenous systems *(section 2.1),* the introduction of new sources of poor data quality *(section 2.2*), and a greater demand for system autonomy *(section 2.3)*. We discuss these challenges individually and highlight, how each impacts the quality of the analytics or the cost-effectivity of the solution.

### 2.1 Data Integration with Heterogenous Systems

In the plate lifecycle data acquisition process depicted in Figure *1*, data acquired via *INTERcheck* is considered internal to the system, since the complete data pipeline lies within the system boundaries of the HCP. By design, this ensures uniform data formats, allowing for standardized data processing. In contrast, *level 1* process data and *level 2* production logistics data from sources external to the system follow the data formats defined by their systems of origin. For instance, semantically identical data points possess different variable names, they may be logged at different precisions or normalized differently.

On the other hand, to make best use of the health indicators provided by health monitoring systems, it must be integrated with a variety of other systems, for instance to be consumed for production logistics management or supply chain management.

None of these examples presents a particularly noteworthy challenge from a technical point of view, yet the precondition to integrate data from multiple different systems threatens to introduce significant engineering overhead and lengthy implementations for each site implementation and ultimately impact, whether the solution is cost-effective.

## 2.2 Data Quality

Throughout the development of HCP there have been significant efforts, to guarantee consistently high data quality and implement robust data normalization techniques, that ensure uniform data. These same guarantees do not hold for data from sources external to the HCP. Common observations include missing values, implausible values due to malfunctioning sensors, and entire cycles missing due to disconnected equipment. Additional data quality issues can be introduced by the human factor in manual process steps, for instance when slide gates are opened or closed following non-standard cylinder movement sequences during the inspection process.

## 2.3 System Autonomy

Not all discussed data quality challenges are unique to the industrialization stage, however, in a data analytics research project, experienced analysts are able to identify them and manage them manually. The industrialization of such analytics demands for a high degree of autonomy of the system, particularly in critical industries like steel production, where equipment is usually disconnected from any external networks and vessels like steel ladles are transported by crane from one working area to the next. A thorough analysis of potential data quality issues is required, to implement rules and algorithms to filter out or correct corrupted data.

The environment and operational circumstances in one steel mill significantly differ to another. Even at one site, operational circumstances may change sharply, due to the dynamic nature of operations. The accuracy of the statistical and machine learning models introduced in *Section 1.1.2* is a result of the data used for their development. Their performance is unreliable, when forced to extrapolate to data out of the known distribution. When deployed in an autonomous system, this imposes, (a) that input data must be continuously monitored to detect unseen data distributions and prevent unreliable predictions, and (b) that feedback loops to the operator must be in-place to continuously monitor prediction quality and automatically trigger updates to existing models based on recent data and operator feedback.

# 3. METHODS

The fundamental design principles, which we discuss in this section, are motivated to ensure the HCP can be deployed quickly as an autonomous system and with minimal data integration overhead at new sites, while remaining adaptable to unique customer needs.

The *plug-in architecture* is an established software development design principle, that allows modular components to be added, removed, or updated without disrupting the core system, enabling seamless integration of new functionalities and data sources while maintaining system stability and adaptability to diverse operational environments. To facilitate data integration and the portability of analytics, the HCP uses this principle as a blueprint for its design, distinguishing between:

- A standard core, including the system’s data management and core analytical functions.
- A standard data ingestion plug-in for the *INTERcheck* data acquisition system.
- Interfaces, enforcing consistent data exchange formats for ingesting data from third-party systems based on the mandatory and optional informational requirements specified by the HCP information model (1.1.1). The integration of external data sources can be realized via plug-ins to these interfaces via common industry standards such as *OPC-UA* and *Telegram* or via direct database access.
- An API layer, enabling the integration of health data into any further systems within a steel mill’s network following the *OpenAPI* standard [7]. The development of custom data adapters is further facilitated by the availability of a Python client library.
- A standard operator-facing application (see Figure 3), optimized for human-machine interfaces (HMI), that displays the distinct classes of plate health data as described in *Section 1.1.2* and provides an intuitive mask for feedback, when a plate is determined to have reached the end of its lifetime.
- A model registry, allowing for the integration of machine learning models from standard frameworks, such as Pytorch [8] and SciKit-Learn [9].

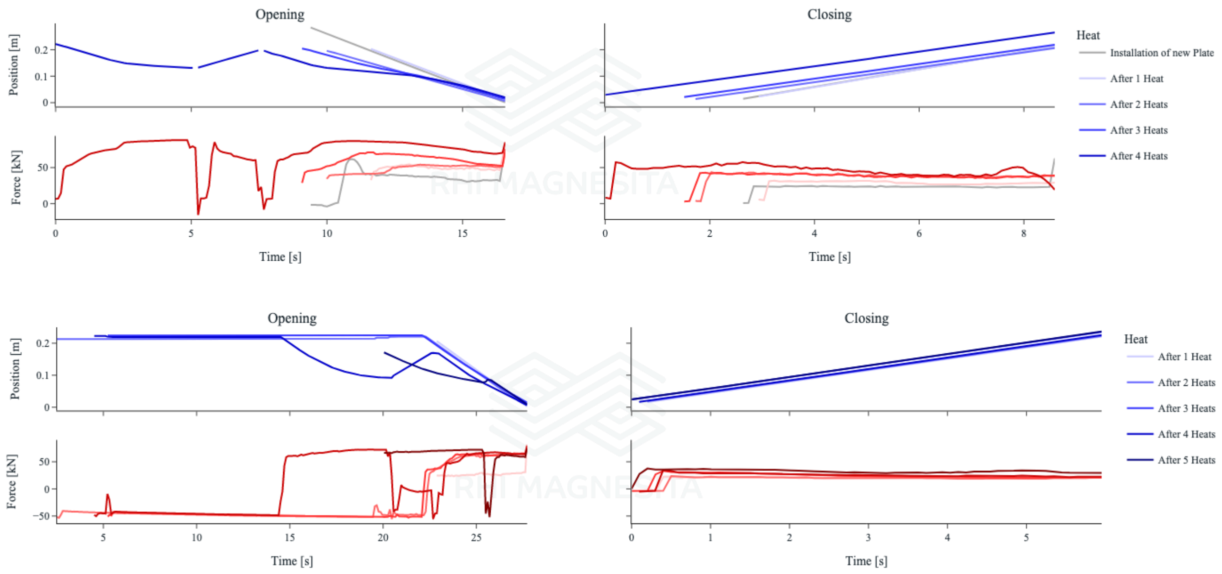


**Figure 2 Examples of data acquired via the *INTERcheck* data acquisition system for two distinct plates, while the slide gates were opened (left) and closed (right) at installation and throughout multiple inspections throughout their lifetimes. Both plates were exchanged after five heats, due to maintenance policies. The first plate (top) was assessed as healthy by refractory experts, the second (bottom) as unhealthy.**

### 3.1 Data Health Checks

Standard data validation techniques, such as checking data types and value ranges, are insufficient to provide guarantees against the data quality issues described in *Section 2.2*. We therefore implement three advanced data quality checks within the HCP analytical framework:

- Data acquired via *INTERcheck* during plate opening and closing cycles is segmented, to determine whether the cycle follows a normal or irregular target trajectory. Irregular cycles are filtered flagged, since they cannot be evaluated by predictive models, due to the lack of references.
- Data is pre-classified by applying a catalogue of rules, designed to flag any issues, that were identified in an expert analysis of potential data quality issues. Examples of issues resulting in shifted or corrupted data are sensor drift or modifications of the process or the system, that are not reflected in HCP information model.

### 3.3 Portability of Analytics

Some analytical functions, such as data normalization and virtual sensor computation cannot be executed correctly, without specific knowledge of the properties of a particular asset. Analytical functions are parametrized accordingly, to enhance the portability of the HCP analytical framework, meaning no engineered analytics should be required to tailor them to system modifications or new sites. For instance, a calculation as simple as transforming the measured pressure value of a hydraulic actuator into the corresponding force transferred to the plate requires knowledge of the specific hydraulic cylinder's cross-section. With the variety of equipment from different vendors typically in use at a single site, this information cannot be assumed, but rather enters the calculation via asset descriptions stored in the HCP information model.

Another measure to enhance the portability of the HCP analytical framework lies in its modularization. Not all data specified by the HCP information model may be available at a given site, for example where some equipment is not instrumented with a required sensor type. For inference, most predictive models require inputs, identical to the data they were fitted with. To ensure that HCP can be introduced with incomplete data integrations or incrementally, we minimize the number of mandatory data integrations to a viable minimum. All further inputs are defined as optional. Therefore, a self-configuration implemented within the analytical framework identifies, which virtual sensors and health indicators can be provided and displayed to operators in any given scenario.

### 3.3 Feedback Loops

HCP relies on *implicit* and *explicit* feedback from the steel mill to: (1) benchmark predictive model performance based on common classification metrics like accuracy, precision, and recall; (2) adjust predictive model parameters to shifted operational circumstances via retraining. *Implicit* feedback regarding operators' decision to reuse or discard a plate enters can be inferred from production logistics data. Information about observed failure modes is not documented in these systems in most steel mills. Hence, the standard HMI application provided to HCP users provides an interface for operators and refractory experts to provide *explicit* feedback. Human feedback which enriches or overrides any inferred feedback, resulting in higher quality datasets.

## 4. RESULTS

The following chapter discusses a reference implementation of HCP at a major European steel mill. We briefly describe how the system was realized and discuss how it is utilized in the steel mill's operations (*Section 4.1*) and for the acquisition of a plate life dataset (*Section 4.2*). Then, we outline how both unsupervised and supervised state-of-the-art machine learning methods were used to train an anomaly detection and a plate health classification model and present our results (*Section 4.3*).

### 4.1 Reference Implementation

The HCP was introduced at the steel mill in October 2023 over the course of one month and has been operational since. The necessary data integrations were realized incrementally via custom data adapters to distinct systems within the steel mill, that provided the necessary *level-1* and *level-2 data*. In accordance with the site's IT-policy, the HCP is deployed within the site's protected network, with no external network connections.

The HCP has continuously provided operators with decision-support information in form of raw data and virtual sensors and health indicators computed within its analytical framework, alongside with information of their progression throughout the plate's past lifetime. All information was made available via the HCP's standard operator-facing application, that can be accessed via HMIs at the LPAs and in web browsers anywhere within the site's protected network.

### 4.2 Plate-Life Dataset

In order to optimize health metrics using real-world data and augment the analytical framework's capabilities in terms of providing automated plate health classifications, the steel mill shared data corresponding to over one thousand plate set lifetimes with RHIM. Where complete lifecycle data was missing, gaps in the data were filled using standard imputation techniques. To enhance data quality, data was manually analyzed and annotated by RHIM refractory experts, including end-of-lifetime failure modes, if evident. Table 1 provides an overview of the most relevant metrics of the resulting dataset. Some samples exhibited relevant failure modes at an early progression. Some samples were annotated as edge cases. These plate sets were demonstrating not yet critical wear patterns, and experts advised, that the reuse decision should remain up to each steel mill's individual policy.

**Table 1 Key metrics describing the plate-life dataset obtained in the reference implementation.**

| | |
|---|---|
| # unique plate sets | 1'157 |
| # samples (plate change decisions at LPA) | 3'838 |
| # healthy samples | 3'260 |
| # unhealthy samples | 49 |
| # edge cases | 5 |

### 4.3 Automated Plate Health Classifications with Machine Learning

We formulate the health assessment as a classification problem – given a plate history, the classifier outputs, whether a plate is to be reused or discarded. All information aggregated over the plate lifetime up to a given point in time are used as inputs to the classifier (and its upstream data preprocessing pipelines). This includes raw data, virtual sensors and health indicators computed in the analytical framework, data from adjacent systems, and contextual information regarding the production process.

Due to its application-oriented focus, we consider implementation details regarding data preprocessing techniques and the machine learning-based classification algorithm's design and training beyond this contribution's intended scope. Figure 2 charts data corresponding to two samples, that were correctly classified as unhealthy and healthy respectively. Characteristically, the force required to open the slide gate during maintenance rises for each heat, especially the fourth heat in the first sample. This plate was prematurely replaced after the fourth heat and evaluated as being in poor condition by an expert. In contrast to that, the measurements for the second samples show a rather constant opening force. The plates were exchanged after the fifth heat according to protocol, but still evaluated as being healthy by the refractory expert.

For a quantitative discussion of results, we consider it important to explain the origin of the presented performance benchmarks in Table 2, so they can be interpreted correctly by the reader. We measure classifier performance via cross-validation by comparing model predictions to the annotations created by RHIM refractory experts. Performance is expressed in terms of common classification metrics: *Accuracy* reflects the percentage of predictions, that coincided with the experts' assessment. The *False Positive Rate (FPR)* reflects the percentage of predictions, where the model would have recommended replacing the current plate, conflicting with the experts' assessment, whereas the *False*

*Negative Rate (FNR)* reflects the percentage of cases where experts recommended exchanging the current plate, that were incorrectly predicted as healthy by the model.

**Table 2 Performance of best classifier obtained via parametrized model search.**

| **Metric** | **Cross-Validation Average** |
|---|---|
| Accuracy | 93.4 % (94.2% without edge cases) |
| False Positive Rate | 8.9 % |
| False Negative Rate | 4.3 % (2.7 % without edge cases) |

In a steel mill's operations these classifier performance metrics could have the following implications in a decision support system:

- *False positives* result in false alarms. If the model's prediction is overruled by the operator's judgement, an excessive FPR will eventually erode trust in the system. It may even bias inexperienced operators to decide to prematurely exchange plates, resulting in an increase of operational costs.
- *False negatives* imply that a potentially unhealthy plate is recommended for reuse. This could result in critical conditions of the plate, leading to steel infiltrations or even breakouts. Even when overruled by the operator, false negatives would result in a massive erosion of trust in the system

If the model's predictions were to be incorporated into a fully automated system, we would face similar consequences. However, with no operator to potentially override both *false negatives* and *false positives*, the risk associated with inaccurate predictions would be significantly enhanced.

Considering that these experimental results were obtained from a dataset corresponding to three measurement campaigns of an individual steel mill, we consider the achievable performance promising from a research standpoint - to achieve these results, we have been able to identify optimized data preprocessing methods and model architectures.

However, for the classifier performance to meet our maturity standards, the classifier performance still requires improvements: (1) With the minimal tolerable level of safety-related risk in a steel mill's operations, we require a FNR of close to zero. (2). To ensure that the model experiences sustained trust and we also aim for a significant reduction of the FPR. These improvements will also allow us to reach the operational cost savings in terms of reduced inspection times and extended plate lifetimes, outweighing costs of premature plate changes.


**Figure 3: The Health Check Platform's operator-facing application makes relevant health indicators, virtual sensors, and sensor measurements accessible via HMI directly at the LPA or via browser anywhere within the steel mill's protected network and provides a feedback interface for experts' assessment of plate health.**

## 5. Conclusion

The first deployment of our platform to a real operational environment, as described in the reference implementation, shed light on the complexity and some of the lesser discussed industrialization challenges of deploying data-driven diagnostics to industrial environments. We highlight how important a comprehensive requirements analysis of market needs is in developing such a solution, due to the need for adaptability to the heterogenous conditions found from one steel mill to another, while keeping data integration and customization efforts at a minimum. The fundamental design choices made within this balance ultimately determine, how fast and at what effort the solution can be deployed to a new steel mill – critical for the solution's cost-effectiveness.

Due to the platform's collaborative conceptualization involving experts with experience in the steel and refractory industry, systems design, and machine learning, many of the fundamental industrialization challenges discussed in this contribution could be anticipated. Other problems in turn had to be solved along the way, including unanticipated sources of data quality issues and difficulties to correctly normalize data, even with respect to proprietary RHIM technology.

Upon observing the platform's usage in the reference implementation, we are confident in our ability to provide steel mills with a solution, that enhances workplace safety, decisional certainty, and the risk of critical situations with important steel plant operational consequences.

Based on the promising classifier performance benchmarks obtained in a real-world environment, we see immense potential in enhancing the platform's plate health prediction capabilities by optimizing the discussed machine learning to a level, where predictions can confidently be considered by automated systems. The platform's ability to curate high quality datasets and its design to integrate machine learning models from a broad spectrum of frameworks creates a formidable foundation to exploit this potential.

## Acknowledgement

We would like to highlight the contributions of *Alpamayo Intelligent Quality Solutions* GmbH, a digital manufacturing solutions provider, in supporting the conceptualization and implementation of the *Health Check Platform* and *CSEM*, a leading Swiss innovation center, in the development and optimization of machine learning algorithms.

Furthermore, we also thank the involved steel mill for their great support.

## References

[1] Silbergasser, H. Ehrengruber, R., Schmidt, V. and Jani M., Proceedings EFRS 2024, 58-62 (2024), 58

[2] Ehrengruber, R., Schmidt, V., Renggli R. and Jani, M. INTERSTOP Automation, Robotics and Digitalization Solutions for Flow Control Technology, RHI Magnesita Bulletin, 51 – 53 (2023), 52

[3] Ehrengruber, R., Bühlmann, R., Schmidt, V. and Persson, M., China's Refractories Vol. 30 2021.2 ISSN1004-4493 CN41-1183/TQ, 33-35 (2021), 33

[4] Schweiger, L., Barth, L., Properties and Characteristics of Digital Twins: Review of Industrial Definitions, SN Computer Science, Volume 4, article number 436 (2023)

[5] Netsch, C., Schöpe, T., Schindele, B., Jayakumar, J., DeepFMEA – A Scalable Framework Harmonizing Process Expertise and Data-Driven PHM, arXiv:2405.08041 [cs.LG]

[6] Mathew, A., Zhang, L., Zhang, S., Ma, L., A Review of the MIMOSA OSA-EAI Database for Condition Monitoring Systems, Proceedings World congress on Engineering Asset Management, 2006

[7] OpenAPI Initiative, OpenAPI Specification, GitHub, https://github.com/OAI/OpenAPI-Specification (Accessed: 25.08.2024)

[8] Paskzke, A., et. al., PyTorch: An Imperatice Style, High-Performance Deep Learning Library, NeurIPS 2019

[9] Pedregosa, F., et.al., Scikit-learn: Machine Learning in Python, Journal of Machine Learning Research (2011)