Monitoring of Ladle Slide Gates in the Steel Industry: Lessons Learned from the Industrialization of Data-Driven Diagnostics in Steel Plants

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ABSTRACT

A data-driven system was developed and implemented to track the condition of ladle slide gate refractories during operation. It supports operators at the ladle wall in their decision-making regarding refractories. Additionally, it provides a robust and reliable system to increase process stability and safety. It optimizes the lifetime of the plates and reduces resource waste and CO_2 emissions.

The framework and methodology presented in this paper offers insights into overcoming the challenges in the industrialization of data-driven solutions within the steel sector like substantial variability of operational contexts in steel plants, stringent data sharing requirements, heterogeneous infrastructure, etc.

Keywords: Condition Monitoring, Predictive Maintenance, Digital Twin, Industrial Edge, Slide Gate Refractories

INTRODUCTION

Figure 1 Ladle wall of an American steel mill.

In recent times, requirements for flow control systems have shifted considerably, prompting the use of robotic cells and digital tools for automated operations at the caster [1]. Meanwhile, at the ladle walls (also called ladle preparation areas - LPA), the processes mostly rely on manual work and the experience of operators to determine when to replace wear parts. One of the main responsibilities at the LPA is to judge if the ladle slide gate plates can be used for another heat—a process known as the "multiple heat check." During this check, operators look for any steel fins (metal protrusions) that can develop between the plates due to slide gate movements. These fins may cause steel infiltrations or even lead to a breakout between the plates. They also use a specialized tool to inspect the casting channel, yet visibility is limited for checking critical wear surfaces.

To mitigate this drawback, certain mills, employ a practice known as the "open check" method. Operators open the slide gate, gaining direct visual access to the working surfaces of both the bottom and slider plates. If the inspection shows the plates are still in acceptable condition, graphite lubricant is applied to the refractory surfaces and the slide gate is closed again without changing the refractory parts. This approach not only aims to prevent serious wear-related issues but also helps to extend the refractory lifetime and reduce consumable costs [2].

Aiming to further improve workplace safety and enhance efficiency through future robotic workflows at the LPA, in collaboration with longstanding partners, we are pioneering a system to monitor the condition of slide gate assemblies and refractories [1]. By using digital twins to capture and analyze data algorithmically, processes can be continuously optimized. Additionally, preserving process knowledge in digital form ensures continuity when experienced workers retire, while adaptive system parameters accommodate unexpected events. Better decision-making will enhance operational reliability, reduce costs, and lower CO_2 emissions. It also accelerates knowledge transfer and operator training [2][3].

Condition Monitoring Platform – a Digital Twin for Refractory Health Monitoring

Digital twins have gained broad acceptance across academia and industry for various digital manufacturing applications. Numerous definitions [4] coexist because these concepts can be applied in multiple ways. In the context of health monitoring, as outlined in [5][6], we define a digital twin of an asset as:

- a process- and equipment-specific information model linking all asset-related data semantically, spanning components, process stages, failure modes, and sensor signals
- sensor, process, and production data unified over the entire asset lifecycle
- a data analytics framework that translates sensor and process data into actionable health insights

The platform adopts this digital twin principle, guiding operators and maintenance personnel through the open check process. It integrates an information model that captures each plate's lifecycle stages, focusing on the most critical elements for assessing wear (Figure 2). It leverages standard sensors and existing data without imposing extra process steps:

1. **Slide Gate Maintenance and Refractory Installation:** At the LPA, the retrofittable INTERcheck system (Figure 2) collects data whenever the slide gate is opened or closed, establishing a baseline for a healthy plate.
2. **Casting Operation:** While the slide gate controls the flow of molten steel into the tundish, INTERcheck continues logging data. These measurements are synchronized with level 1 data — e.g., tundish level control (TLC). Production logistics data (level 2), including melt chemistry, also feeds into the digital twin, since chemical composition strongly affects plate wear.
3. **Routine Maintenance and Inspection:** After each heat, the slide gate is cycled in the same way as in *step 1*. INTERcheck records the response, and the operator's decision to reuse or discard the plate is documented, together with any identified failure mechanism.

In large facilities multiple LPAs operate simultaneously and synchronizing these data streams requires level 2 data integration. To give operators actionable insights on determining whether to reuse or replace plates, operators and refractory experts defined several analytical requirements in the form of virtual sensors:

- Casting duration
- Steel erosion index (based on Ca, Mn, C, etc.)
- Slide gate operating force
- Transfer time from caster to LPA, and others

Tracking these health indicators over multiple cycles is critical for effective interpretation. Predictive models are also vital for enhancing decision-making and paving the way toward automation, given each mill's unique operating conditions.

In our previous work [7], we introduced the core design of the platform and shared promising results from a steel manufacturing facility. For example, the system correctly identified unhealthy plates about 93.4% of the time—with an 8.9% rate of false alarms (when the system's assessment of an unhealthy condition of the slide gate stood in contrast to a refractory expert's assessment) and a 4.3% rate of missed warnings (when the system fails to flag a real issue identified by experts). Building on these encouraging findings, our current study explores both the potential benefits and the challenges of sharing data from equipment manufacturers and steel plants. This integration is key for the long-term optimization of advanced predictive maintenance analytics and the adaption of models to site- or asset-specific profiles. In Section 2, we outline the main factors that make it necessary to balance cloud-based processing with on-site (edge) computing in flexible, hybrid architectures. Section 3 then explains how the platform's modular, composable design supports deployment at the industrial edge, and we illustrate this approach with a case study from an American steel mill.

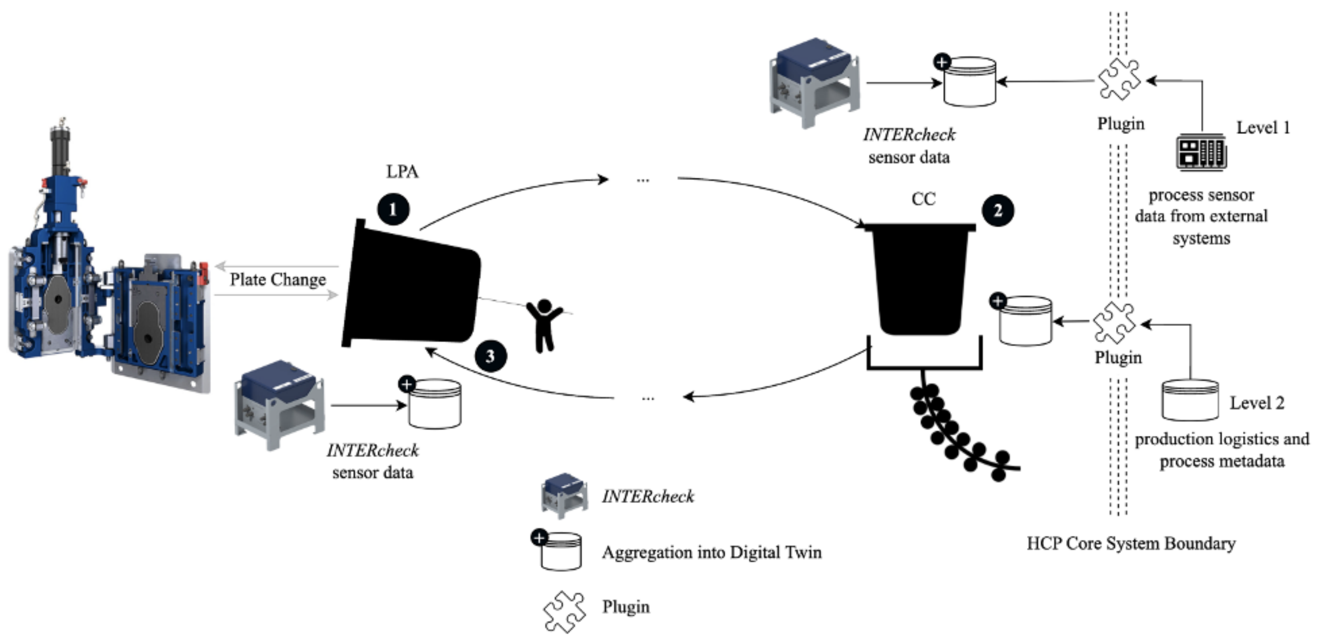

Figure 2 Data defined by the platform's information model is aggregated in each plate's digital twin as the plate circulates through relevant process steps of the steel casting process.

PLATFORM DESIGN AS A KEY FACTOR TO OVERCOMING CHALLENGES OF DATA INTEGRATION IN THE STEEL MANUFACTURING VALUE CHAIN

Many organizations have embraced digitalization efforts, yet, particularly for predictive maintenance, industrial adoption often remains slow [9], particularly due to limited data availability: Failure occurrences are relatively rare events, making it difficult to compile the extensive datasets needed to train machine learning (ML) models.

Enhanced data integration between equipment suppliers and steel manufacturers can potentially unlock otherwise inaccessible operational improvements. From the supplier's perspective, data insights gathered at the edge offer opportunities to refine product design, boost reliability, and support sustainable engineering. From the steel producer's perspective, on-premise analytics allow timely decision-making and improved plant availability. [9][10][12].

Equipment manufacturers that aim to provide meaningful data-driven maintenance or predictive analytics solutions must be able to (a) assemble large, high-quality datasets, and (b) deliver scalable offerings that integrate seamlessly with the diverse platforms and networks found in steel plants. Our platform design process, has identified key factors, defining requirements for a *plug-in architecture*, enabling the efficient and secure integration of the platform with steel manufacturing plants' heterogenous IT systems and third-party equipment, both as sources and consumers of data. Our practical experience collected from deployments of the platform at various operational steel plants indicate an additional requirement to deploy the platform directly at the industrial edge or in hybrid architectures, leveraging on-premise and cloud infrastructure:

1. **Heterogeneous and Dynamic Environments**: Each steel mill's operational landscape can differ substantially, making uniform data collection or model deployment challenging. Even within a single steel plant, conditions may vary depending on factors like equipment type, maintenance practices, or product mix. By deploying analytics at the edge, solutions can adapt to site- or asset-specific profiles in real time, applying context-sensitive data normalization and ensuring that local changes do not compromise the broader system's performance.
2. **Data Sovereignty and Security:** Since steel plants often fall under the umbrella of critical infrastructure, tight cybersecurity policies severely limit or even prohibit external network connections [10][11]. At the same time, data sharing is minimized to protect trade secrets in a competitive market. Consequently, the platform is designed to meet latest security standards and implements best practices in data governance, software and system security as well as software and system updates.
3. **Cost of Data Integration**: Like most predictive maintenance analytics, our platform merges various data streams like operator inputs, production logistics, process parameters, and sensor feeds into a single architecture. Data from third-party systems can be integrated in and consumed directly at the edge, keeping integration efforts for the steel manufacturer's IT departments at a minimum.

Section 4 illustrates how the platform was installed at the industrial edge at an American steel mill—an environment characterized by strict security and a policy of minimal external connectivity. To satisfy these requirements, the original platform architecture (as presented in our previous publication) was refined to follow the principles of a **composable architecture**, allowing the system to run autonomously on edge infrastructure, while still enabling **selective data exchange** with cloud services when needed. In our previous work, the **platform architecture** was introduced as a modular structure:

- A standard core to manage data flow and essential analytics.
- Data ingestion plug-ins to integrate sensor or production data.
- APIs and interfaces that ensure consistency with third-party systems.
- An operator-facing application and a model registry for machine learning.

However, the concept of a **composable architecture** goes one step further: it formalizes how each service within the platform (i.e. a database, a computation service, or a user interface) can be independently deployed, scaled, and updated, and how these components communicate without tight interdependencies. In practical terms the development implies:

- Core Services vs. Optional Services: analytics and data management core remains mandatory. Additional features (e.g., data source connectors, databases, cloud connectors, ML model inference services) are packaged as optional services, which can be activated, omitted or replaced based on site requirements.
- Containerization: Each service runs in a dedicated container, isolating it from others and enabling continuous feature updates, security updates, optional remote maintenance and resource management.
- Internal Communication: Services communicate via well-defined interfaces (e.g., REST APIs), ensuring the overall system behavior remains independent of the number and type of deployed services. The composable approach provides enhanced flexibility by allowing the platform's architecture to be tailored to each steel mill's unique environment, while maintaining internal consistency and predictable interfaces. This design ensures the platform remains lightweight for deployments on edge infrastructure. (Figure 5).

CASE STUDY – DEPLOYING THE HEALTH CHECK PLATFORM AT THE INDUSTRIAL EDGE

At the steel mill, data sovereignty and operational security were key concerns. As a major steel producer, the plant's Operational Technology (OT) environment is critical to production continuity and cannot risk external intrusions. Additionally, the facility aimed to minimize IT workload when integrating new technologies. This led to four main decisions:

- **Installation:** A single, prepackaged edge device was delivered to site, containing the full platform software stack in containerized form, which was installed at LPA (as depicted in Figure 3). Local IT mapped local data endpoints (e.g., hydraulic actuator sensors, production databases) to the edge device's interfaces.
- **Data Ingestion, Processing & Storage:** Data ingestion and preprocessing (including the advanced data quality checks from section 3 of our previous publication) happen autonomously at the edge. By default, data is stored in a timeseries database and contextualized via references in a relational database, both hosted at the edge.
- **Selective Cloud Integration:** Aggregated or anonymized data is forwarded to cloud services only when necessary, supporting long-term trend analysis and model refinement without compromising on data sovereignty or cybersecurity requirements.
- **Security Model:** All internal data remains on the edge device unless explicitly exported; no other network paths are exposed. VPN tunnels enable remote troubleshooting and updates, isolating the plant's OT environment from any external security threats.

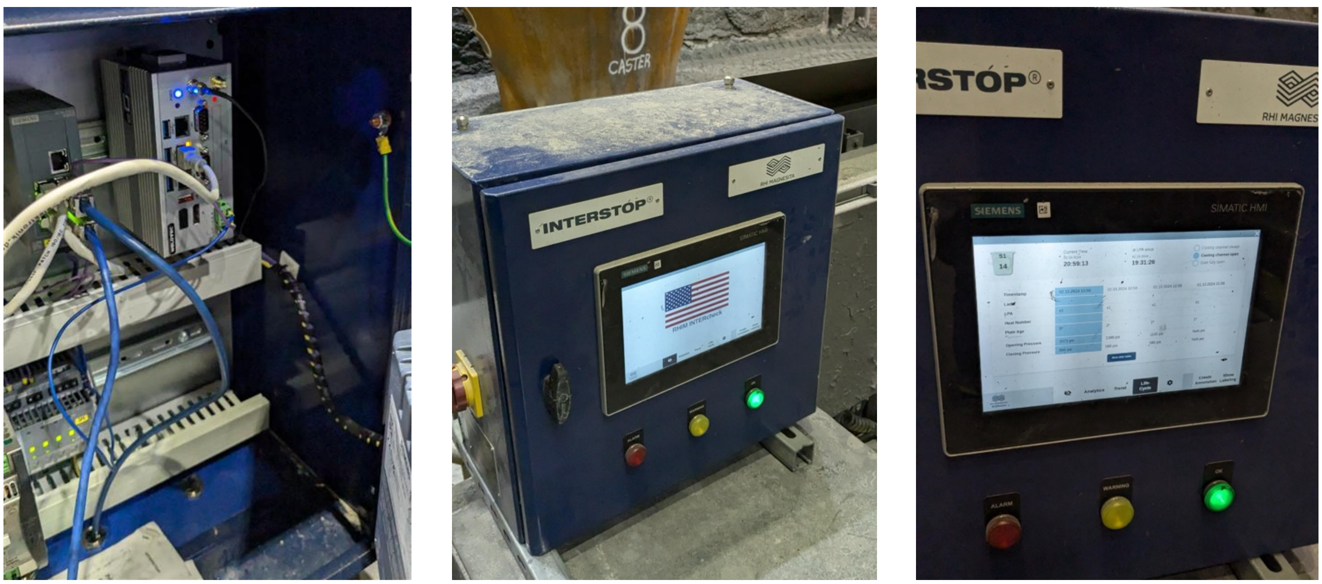

Figure 3 The platform is prepackaged on an edge computer designed for demanding industrial environments and installed at the LPA (left). Its operator-facing application (center, right) makes relevant health indicators, virtual sensors, and sensor measurements accessible via HMI directly at the LPA or via browser anywhere within the steel mill's protected network and provides a feedback interface for experts' assessment of plate health.

The platform was deployed at the site in October 2024. We observed several benefits particular to the platform's design updates as described in Section 3:

- **Reduced Integration Complexity & IT Management Overhead:** The prepackaged solution allowed a "plug-and-play" deployment with minimal configuration demands on local IT. It also simplified the task of monitoring on-premise resources consumed by the system. Furthermore, local IT teams can delegate management of the platform to the supplier without concerns about granting access to critical IT infrastructure. Arguably, the simplicity of the solution also increases cyber-security and simplifies audits by minimizing any attack surface.
- **Extensibility:** Additional modules, like ML model inference services or new data source interfaces can be enabled later without a major system overhaul.
- **OT/IT-Security:** The system runs reliably without continuous external connections, aligning with the plant's strict security stance. In cases, where the plant's operations benefit from advanced analytics insights from the supplier, edge-to-cloud architectures support selective data sharing. Data can be filtered or pseudonymized locally, letting the supplier refine models without exposing sensitive operational details. Since, by design, the edge deployment limits

supplier's access to the platform via secure VPN, complex user management and resource-based access authorization is simplified for local IT.

Since the platform's introduction in October 2024, we have collected data on 115 distinct plate lifecycles. However, 96% of these samples still do not meet the data quality standards needed for the platform's machine learning algorithms. The primary issue is missing contextual inputs, identified in our previous publication as crucial for accurate predictions. Much of this gap can be traced to manual data entry steps in the casting process (see Figure 2). We anticipate that ongoing improvements to the data acquisition workflow will substantially raise data quality in the next few months.

Our analysis of sensor data - particularly the work required to open the slide gate - suggests a marked drop in friction after the open check (Figure 4), consistent with the maintenance performed during that procedure. Compared to other datasets, such as the dataset discussed in our previous publication, this plant uses different hydraulic equipment and follows different standard operating procedures. Notably, the mill has adopted the open check procedure and often extends plate usage beyond six heats, whereas the other site routinely discards plates after five. While we observe comparable general trends and can robustly detect and extract maintenance cycles from logged data, variations lead to distributional shifts between datasets acquired at individual sites.

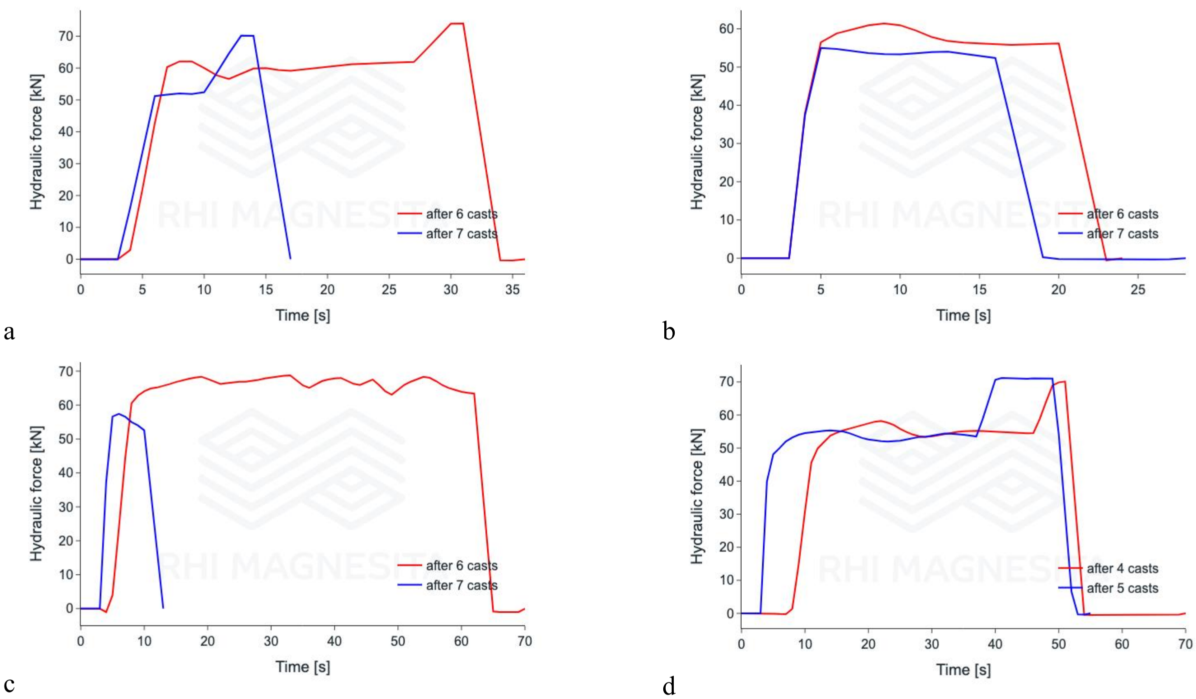

Figure 4 The slide gate opening force is logged, whenever the slide gate is opened or closed for casting or for inspections at the LPA. The *open check* inspection and maintenance procedure, designed to extend plate lifetimes, was adopted by the steel mill. Examples a-d show samples acquired when opening the slide gate prior to (red) and post open check. Examples a-c show a reduced maximum opening force, paired with significant increases in the slide gate opening velocity. The observations indicate that slide gate friction is reduced as an effect of steel fin removal and the application of graphite lubricant during the routine checks.

LESSONS LEARNED FROM THE PLATFORM DEPLOYMENT

Distributional shifts between plants - and even within a single plant over time - have a significant impact on the performance of machine learning algorithms. As discussed in our previous work, input features such as the force or work required to open and close the slide gate can be highly predictive of plate health, but their effectiveness depends on matching the local operating context. To achieve robust generalization, large cross-sectional datasets that span multiple facilities are needed. When data is limited, domain adaptation strategies, like fine-tuning a model with site-specific data, can increase predictive performance.

Both approaches demand a curated pool of sensor, process, and operator feedback data. Consequently, closer integration between steel manufacturers and equipment providers can be beneficial to efficiently building datasets with strong predictive value.

Our experience also shows that equipment manufacturers, through thoughtful design decisions, can actively facilitate this data integration. Initially, however, operator acceptance and layout constraints must be addressed, to not to disrupt current workflows. In our case, the installation initially reduced working space near the operator station, which was later remedied to ensure the operator's daily routines remained unchanged. Likewise, aggregating key information during the initial training phase proved more challenging than expected. The system relied on operators to select the active ladle. Additional data, such as refractory age, casting duration, and steel composition—was collected manually by experts using standardized worksheets. This manual linkage of disparate data sources underscores the importance of having integration solutions in place from the outset, allowing data to be automatically collected and aligned with mill operations.

Furthermore, our findings highlight how customer-specific processes, in this case, the open check procedure and reliance on Electric Arc Furnace (EAF) production can influence measured results, prompting adjustments to the platform's data model. Successful rollouts also depend on clear communication among all stakeholders, including early involvement of IT and security teams from both the steel producer and the equipment supplier, to ensure that edge devices and network configurations meet all operational and cybersecurity requirements prior to installation.

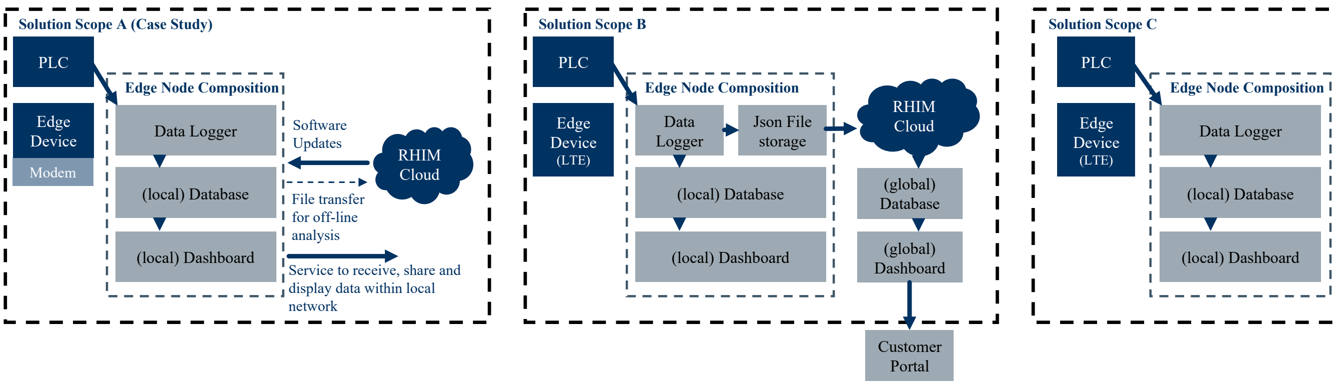

Figure 5 The composable architecture of the edge node allows for versatile deployments of the platform, making use of edge, on-premise, and cloud infrastructure. *Solution Scope A* (left) depicts the selected edge node composition at the American steel mill, whereas *Solution Scope B* (center) and *C* (right) depict alternative edge node composition, determined to fulfill varying functional requirements and conditions.

In our case, the platform was enhanced to operate as a composable edge node, a physical or virtual machine located at the boundary of a network that manages local data collection, on-site analytics, and secure communication with external systems. The versatility stemming from the composable architecture of the edge node not only addresses the data sovereignty and heterogeneity challenges of steel manufacturing plants but also supports other industrial scenarios with minimal customization:

- **Temperature Monitoring on Steel Plant Aggregates**: The edge node locally aggregates temperature data and can feed operator dashboards and the supplier customer portal, which enriches it with additional data (e.g., 3D scans) for holistic process monitoring (see also Figure 5, *Solution Scope B*).
- **Gas Purging Operation**: Optimizing gas purging operations benefits from on-site analytics for root cause analysis and real-time monitoring, with the framework adapted to meet safety and environment-specific constraints (see also Figure 5, *Solution Scope C*).

Our experiences motivate us to further standardize core services (data ingestion, validation, and analytics) while maintaining flexibility and extensibility to accommodate steel manufacturing plants' distinctive and continuously changing business needs. By striking the right balance between standardized components and site-specific adaptations, solutions like the platform discussed here, we can handle distributional shifts effectively while minimizing the burden on plant operations.

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