



## **Digital Twin + Industrial Internet for Smart Manufacturing: A Case Study in the Steel Industry**

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## 1. THE INDUSTRIAL INTERNET

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The Industrial Internet and Smart Manufacturing can be viewed as a twin-movement in the larger context of industrial digital transformation. They focus on applying advances in communication and computation technologies in industrial processes to enable new capabilities and optimize operations. These new technological advances include cloud computing, big data, machine learning/artificial intelligence and new communication technologies, which have been developed in the recent decades and used widely in the consumer and commercial internet. Enabled by these new technologies, the Industrial Internet seeks to optimize industrial and manufacturing operations by applying insights from analytics on the vast amount of data collected from the newly connected equipment and systems. On the other hand, Smart Manufacturing seeks to fully integrate manufacturing systems and processes so that they can be optimized by use of information—or information driven optimization of manufacturing.<sup>1</sup> Laying its foundation in connectivity and data analytics, which are needed for integrating systems and optimization by information,

the Industrial Internet enables Smart Manufacturing to optimize production operations across various manufacturing processes. Leveraging these new digitalization capabilities, industrial enterprises can achieve high flexibility, agility and efficiency; improve total performance in their production and business operations; create new service capabilities and business models and finally seek transformational outcomes.<sup>2</sup>

## 2. DATA, ANALYTICS AND APPLICATION: CLOSED LOOP OPTIMIZATION FOR THE INDUSTRIAL INTERNET

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To optimize industrial operations is to make optimal decisions in response to changes, with and without a human in the loop, in operational or manufacturing processes. To achieve this, we need access to the right information at the right time about the market, about the customers and the workforce, about the processes and finally about the physical assets and their operating environment. Gaining insights about the industrial assets and their operations is where the Industrial Internet keenly focuses on.

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<sup>1</sup> For a general perspectives of Industry 4.0 and smart manufacturing, including architecture for integrating manufacturing systems and processes, "Reference Architecture Model," ZVEI – German Electrical and Electronic Manufacturers' Association, Frankfurt, 2015.

<sup>2</sup> For an overview of the impact of the Industrial Internet of Things, World Economic Forum, "Industrial Internet of Things: Unleashing the Potential of Connected Products and Devices," World Economic Forum, January 2015.

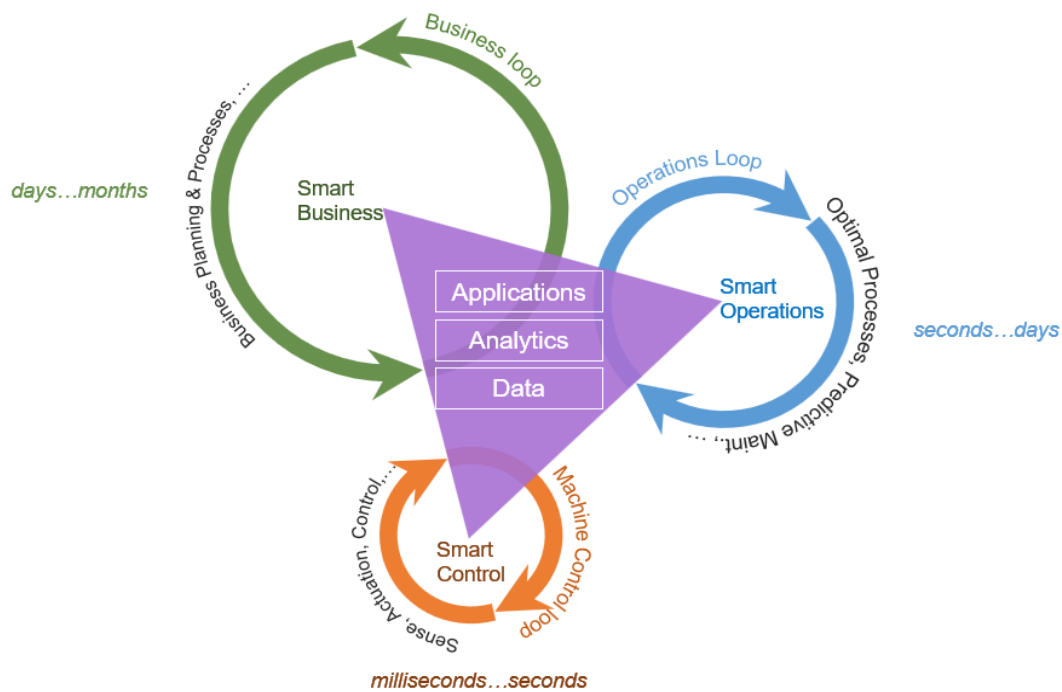


Figure 1: Closed loops of optimization enabled by data, analytic models and applications

Therefore, the Industrial Internet is more than just connecting to the industrial assets. It is about building on that connectivity to collect data and apply data analytics to gain insights and transform these insights into actions that are applied to the individual machines, the operations of fleets of machines and to the business processes—ultimately to bring intelligence in the overall end-to-end business processes to achieve optimal business outcomes. It may not be an over-simplification to say that the core elements in the application of the Industrial Internet are data, analytics and applications that form closed feedback loops to enable smart and optimal operations. Here, applications refer to the software that incorporates the business logics which transform the insights from data analytics into actions.

This data-driven closed-loop optimization can in fact be implemented in multiple loops, as shown in Figure 1. The control loop optimizes the operation of individual equipment with a response near real time in the milliseconds to ensure the equipment is operating—and doing so efficiently for higher output at lower cost (e.g. in energy). The operation loop optimizes the operation of a fleet of equipment (e.g. across a production line, or even across production processes) with a response time ranging from seconds to hours to seek balanced and efficient operations. The business loop optimizes business operations in a response time ranging from hours to weeks to seek to maximize value-creation by cross-domain (e.g. equipment maintenance, process management, energy management, quality management, etc.), multi-factor (e.g. cost,

quality, productivity, delivery time, etc.) and optimization (e.g. achieving zero-inventory on-demand production).

In summary, the key to the Industrial Internet, including its applications in a manufacturing setting, is how to implement data-driven optimization via the data, analytics (model) and closed-loop application to solve specific problems in various industrial scenarios.

### **3. APPLYING THE INDUSTRIAL INTERNET FOR SMART MANUFACTURING**

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Applying the core idea of the Industrial Internet in a manufacturing environment requires data, analytics and application in the following ways:

- Data is about connecting to the various types of equipment and systems—including PLCs, SCADA, DCS and PCS—and other manufacturing software systems, such as MES, QMS, ERP and PLM, to collect data about the production material and parts, the products as they are being manufactured, the production equipment and processes, the workers, the product design and the business processes.
- Analytics (Model) include building and applying various analytic models to analyze the data and gain insights about the operational states of the equipment and production processes. The depth of the analytics increases from descriptive (e.g. what happens in remote

monitoring), diagnostic (e.g. understanding why it happens), predictive (what and when it will happen) and prescriptive (how to respond to a predicted event)—and the analytics have become more sophisticated.

- Application involves implementing business logic that transforms the insights from the analytics into optimal decisions and actions, either providing recommendations of action to the operators (humans in the loop) or directly instruct the systems to complete the closed feedback loop of optimization in the production processes.

### **4. ARCHITECTURAL AND SYSTEMATIC CHALLENGES**

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Manufacturing systems are complex systems, often involving a large number of interconnected equipment and many intertwining processes working in concert. For example, in a typical setting in the iron and steel industry, a continuing process manufacturing sector, a steel plant has a long and complex end-to-end production process consisting of many sub-processes including sintering, ironmaking (blast furnace), steelmaking (converter), continuous casting, heat treatment, hot rolling, cold rolling and strip processing. Each of these sub-processes operates dozens of various equipment pieces in a complex production process. Furthermore, these processes run at various rhythms and paces ranging from a continuous process at an early stage (e.g. iron making) to a discrete process at a later stage (e.g.

striping). Through the end-to-end production process, there are intertwined material, energy, information and value flows across these sub-processes.

Implementing data-driven optimization in such a large-scale manufacturing environment faces several major challenges.

Building on the foundation of automation systems over the past few decades, various information systems (software applications) have been implemented to manage one or another aspect of the complex production process (application domain). The software has proven valuable in managing the planning and execution of the manufacturing processes, quality, energy efficiency and equipment (asset) maintenance. Often, the same type of software applications (e.g. quality management) are implemented for different sub-processes. On the other hand, most of these software applications have been implemented based on the conventional hierarchical architecture

patterns, such as ISA-95. This often results in isolated software applications each requiring a separate and dedicated stack that includes a server hardware, operating system, databases and software implementing the specific business logic. Moreover, because many of these software applications are highly customized, they tend to be closed-systems that are not intended to be interoperable with other systems. This leads to the formation of application islands and data silos, as illustrated in Figure ). This situation makes the integration among the application islands and data silos a daunting, if not nearly impossible, task. However, this type of integration is exactly what is required to achieve a higher level of optimization across various equipment in a sub-process and across sub-processes.

For example, in order to provide a closed-loop optimization over manufacturing process engineering for the purpose of finding the optimal set of process engineering parameters, it needs to obtain

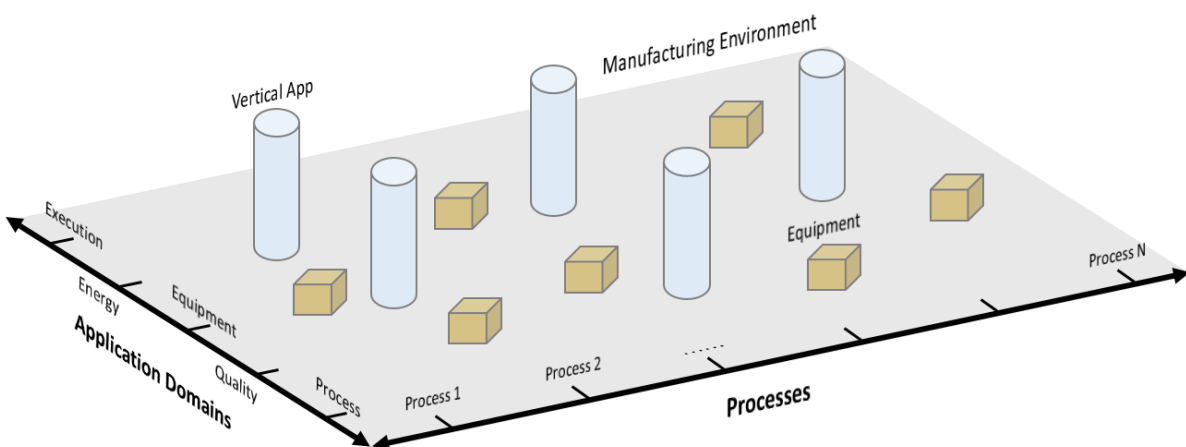


Figure 2: Application islands and data silos in manufacturing application environments

feedback from various operational domains. Based on our experience, the feedback first and foremost comes from product quality, followed by energy consumption, material supply, equipment conditions and up-stream and down-stream sub-processes. This feedback helps determine the best set of engineering parameters for meeting product quality, lower energy and material consumption and achieve a higher production rate.

On the other hand, to realize data-driven optimization, the analytics become more involved—progressing from descriptive to diagnostic, predictive and prescriptive. Its scope also expands from analyzing a single asset (e.g. in the case of predictive maintenance) to a fleet of assets (e.g. in a production line, or even across production sub-processes such as sintering and casting in an iron-and-steel manufacturing process). This type of analytics relies on data collected

from a fleet of assets that are well-organized in association with each other. The required level of complexity in analytics is clearly increased as a result (Figure 3). The fragmented data silos—as well as the absence of a systematic description in the digital space of complex production environment analytics found in many manufacturing environments today—together present a great obstacle to achieve in-depth collaborative analytics. In other words, we need a systematic approach to represent the real world in the digital space and facilitate these sophisticated analytics.

## 5. DIGITAL TWIN

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The concept of digital twin has garnered increasing attention in the recent years because it can be used to systematically describe the real world, including physical assets and logical processes, in the digital space.

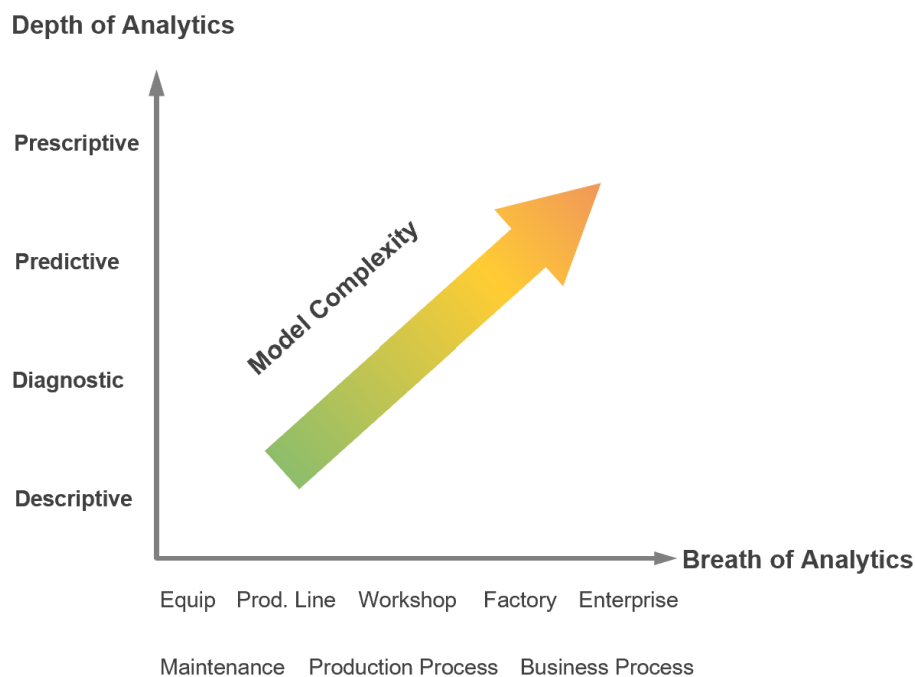


Figure 3: Increasing Analytics Complexity

As a pragmatic definition, a digital twin is a full lifecycle dynamic digital replica of a physical or logical object in the real world. Examples of physical objects include valves, motors, machine tools, production lines, workshops, factories, etc.; and examples of logical objects include production processes, logistics processes and organizations.<sup>3</sup>

First, a digital twin contains data collected from and about its physical counterpart, spanning its full lifecycle. The data includes the as-designed data (product design specifications, process and engineering data), as-manufactured data (production equipment, material, method, quality data and operators), and as-maintained data (real-time and historical configuration and operation state data, and maintenance records) of the real-world counterpart. The data may also include transactional records about a piece of equipment, for example.

Secondly, a digital twin contains a variety of computational or analytic models pertaining to its real-world counterpart, ranging from

first-principle-oriented (natural laws), data-oriented (statistical, machine learning/artificial intelligence) and geometrical or visualization-oriented (3D modelling and augmented reality).

Lastly, a digital twin provides service interfaces for software applications to access its data and invoke its models.

Such a digital twin construct organizes and enables access to data in association with its corresponding real-world objects from an OT perspective, rather than the usual data tables in databases from an IT perspective, making it more logical and thus easier for running analytics models and developing applications.

The connection between a digital twin and its real-world counterpart is dynamic, possibly real-time and bi-directional (see Figure 4). Sensor data and operational states of the real-world object are continuously sent to the digital twin, and any instructions or commands resulting from decisions from

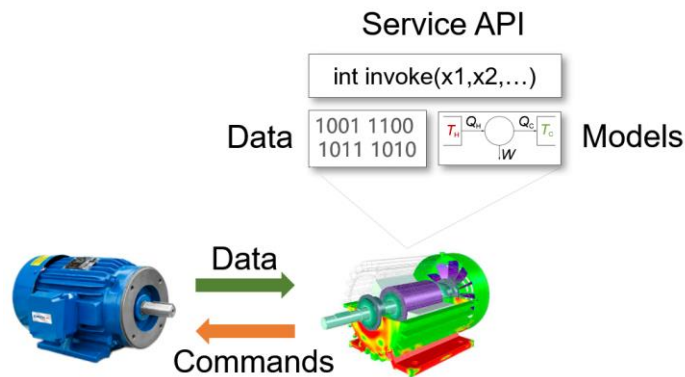


Figure 4: Digital Twin

<sup>3</sup> For a general and broad definition of digital twin, "Industrial Internet Vocabulary, V2.0" Industrial Internet Consortium, Boston, 2019.



the analytics in the specific operational and business context would be sent back to the real-world object to be executed.

With a digital twin, therefore, we can describe, simulate and predict the state and behavior of its real-world counterpart based on analytics on historical and real-time data—and we can consequently optimally respond to changing conditions of the real-world counterpart.

Furthermore, if we define a common construct (data, models and service API) for digital twins, we can build digital twins for components and from them construct digital twins for equipment, production lines, workshops, factories and even enterprises—just like we construct these entities in the real world. Digital twin thus offers a systematic approach to represent complex real-world systems—including those in the manufacturing environment and digital space—building comprehensive digital factories, as depicted in Figure 5.

## 6. INDUSTRIAL INTERNET PLATFORM AS AN INDUSTRIAL DATA OPERATING SYSTEM

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An Industrial Internet platform that is built with the latest advanced technologies—including Cloud Computing, Big Data and machine learning/Artificial Intelligence—offers great potential to rethink traditional digital architecture in the manufacturing environment, find new ways to bridge the application islands and channel data silos as described previously, enable holistic data-driven optimization across manufacturing applications and processes and more importantly enable a new breed of data-driven smart industrial applications.

For example, cloud computing technologies built on the foundation of virtualization—including containerization and dynamic workload orchestration technologies—enable large-scale computation capabilities on demand with unprecedented scalability,

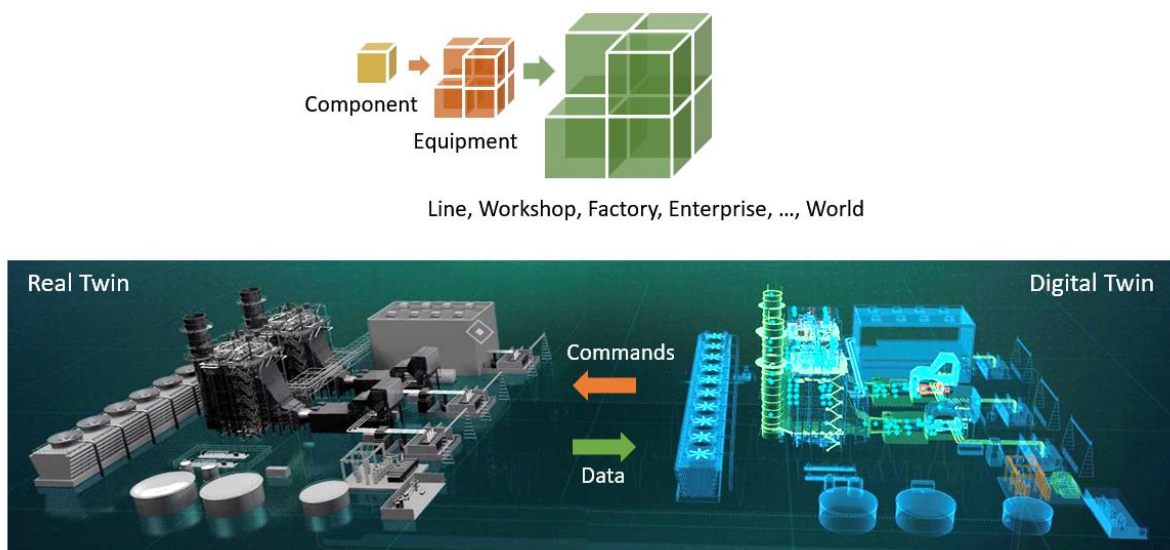


Figure 5: Digital Factory Representation built from Digital Twin

accessibility, availability and elasticity at low cost through economies of scale. Furthermore, these technologies have matured, making it feasible to deploy in small datacenters and small clusters of servers to enable small-scale distributed computing on the edge in the manufacturing environment—with the benefits of scalability, reliability and ease of management. On the other hand, due to the large amount of data expected to be stored and managed in the manufacturing environment, scale-out capabilities in big data are needed. Finally, machine learning modeling has increasingly become an analytic capability mutually supplementing the traditional first-principle-oriented modeling. Introducing machine learning capabilities in the manufacturing environment has become fruitful.

Built on such a broad set of technologies as outlined above, an Industrial Internet platform for the manufacturing environment should seek to abstract a set of common functions that are required and shared by data-driven smart software applications and offer them as horizontal platform services to reduce the otherwise repetitive implementation of these functions in conventional architectures. These key common platform functions coincide with core elements of the Industrial Internet, namely data, analytical models and applications (implementing business logics).

The data framework offers unified data collecting, processing and storing capabilities to achieve full lifecycle management of production data, avoiding the data silos commonly found in existing manufacturing environments.

Analytical model frameworks offer a unified execution framework that draws data from the data framework below it, running multiple analytic models as plug-ins simultaneously and efficiently.

To complete closed feedback loops, insights drawn from the data analytics are combined with operational and business logics to transform into actions. Often, there are many applications involved in manufacturing processes. To avoid building new chimney-like closed applications, these applications are run and managed in a unified application development and operation (DevOps) environment. Such an environment would enhance the reliability of applications, decrease the effort in application development and reduce the complexity of system operations and maintenance management.

Furthermore, a *Digital Twin framework* offers a unified, systematic approach to represent, configure and manage the real-world objects in the digital space. It also provides a unified interface to the real-world objects for application development, akin to

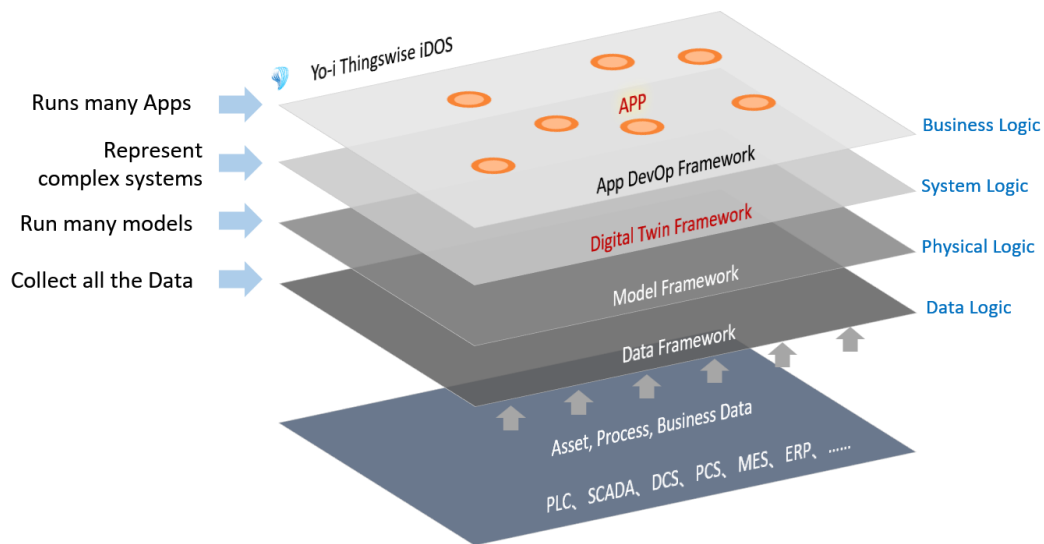


Figure 6: Industrial Internet platform with Digital Twin Framework as data-driven operating platform

the interface concept in object-oriented programming, thus simplifying application developments by isolating the application developers from the complexity of the physical world.

Envisioned here is a new class of data-driven industrial operating platforms as illustrated in Figure 6, encompassing the requisite architectural elements discussed above in reference to and consistent with the functional domain architecture of the Industrial Internet Reference Architecture<sup>4</sup> published by the Industrial Internet Consortium. It is built on recent advances in cloud computing, big data and machine learning/Artificial Intelligence technologies and provides a clear and simple horizontally layered architecture that abstracts out the common core capabilities required by data-driven intelligent industrial applications. This

horizontally layered architecture consists of the loosely coupled data, model and application frameworks unified by a digital twin framework. Because of its cloud computing origin, this architecture is inherently scalable and reliable and enables easy data integration, model execution and application DevOp. It is flexible to be deployed in various environments, e.g. public clouds, private clouds or even on the edge (as in the manufacturing environment), providing the necessary performance, security and control. At the end, such an architecture would incorporate an increasing array of GUI-based tools, making the development of data-driven industrial applications simpler, at shorter cycles and lowered cost, thus making the Industrial Internet more economically applicable to a larger number of manufacturing settings.

<sup>4</sup> "Industrial Internet Reference Architecture," Industrial Internet Consortium, Boston, 2017.

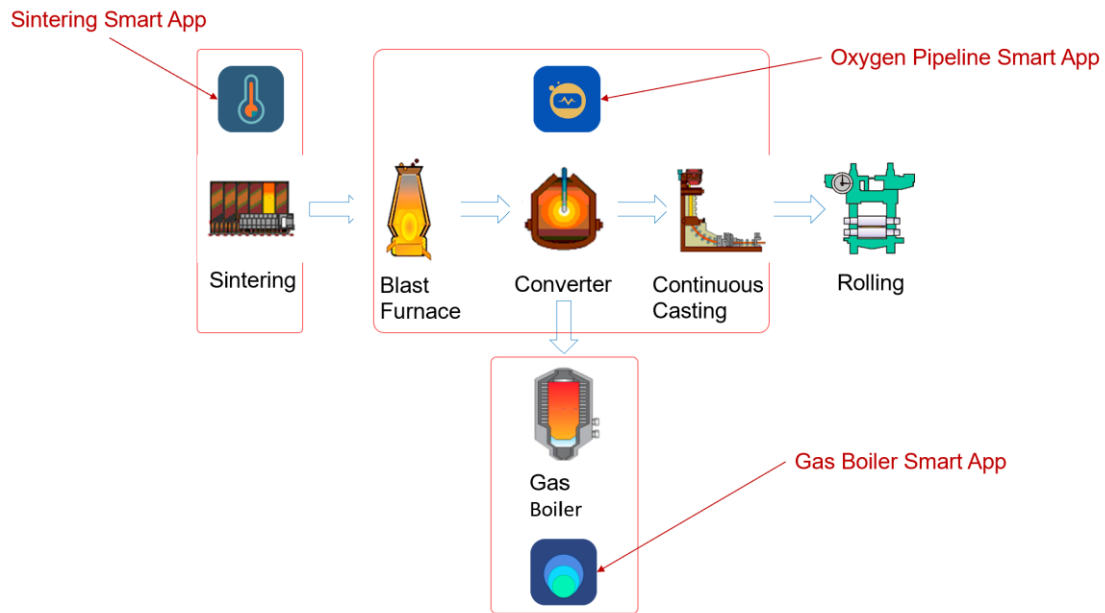


Figure 7: Smart Apps for the iron-and-steel plant

With such a horizontally scalable Industrial Internet platform deployed in a manufacturing environment, no matter how complex and large it is, the complete production assets and processes can be represented, configured and managed with the Digital Twin Framework. Data across all assets, processes and systems can be gathered, pre-processed, stored and managed into a single data framework. Supported by such a framework, many data analytic models can be run and managed within that single model framework. Relying on the Digital Twin Framework, many software applications can be developed, run and maintained within a single application DevOp framework.

## 7. USE CASE IN AN IRON-AND-STEEL PLANT

We deployed the Yo-i Thingswise iDOS, an Industrial Internet platform with a digital twin framework—based on the architecture framework described above—in an iron-and-steel plant. This plant has an approximately 300 metric-ton production capacity located in Shandong, China.

Just like a typical iron-and-steel plant, this plant has a high level of automation implemented in the production equipment. The platform collects data mostly from automation systems such as SCADAs and industrial meters measuring temperature, pressure and flow-rate.

Based on the potential return of value, we developed and installed a number of smart

apps in the platform that focus on optimizing a number of sub-processes in the plant.

In this article, we describe the smart apps as depicted in Figure , which include:

- Sintering Smart App: sintering machine terminal temperature prediction and operation recommendation;
- Gas Boiler Smart App: gas boiler thermal efficiency optimization; and
- Oxygen Pipeline Smart App: oxygen pipeline supply and consumption balance optimization.

Though each of these apps addresses a different problem across different production sub-processes, they share a common theme, which includes:

- They are built on the same digital twin system covering the sub-processes that are involved. Once

being defined and configured, the digital twin system supports various analytics models and applications across these sub-processes.

- Predictive and prescriptive analytics are performed on data collected from equipment in the relevant sub-processes.
- Analytic outcomes are combined with business logics to arrive at role-based operational recommendations targeted toward specific operators.
- The data analytics run continuously with internal data collection in order of seconds, dynamically reflecting the real-world condition. Operational recommendations are provided to specific operators as necessary.
- While the first two apps (sintering and gas boiler) focus on optimization in a single sub-process, the oxygen

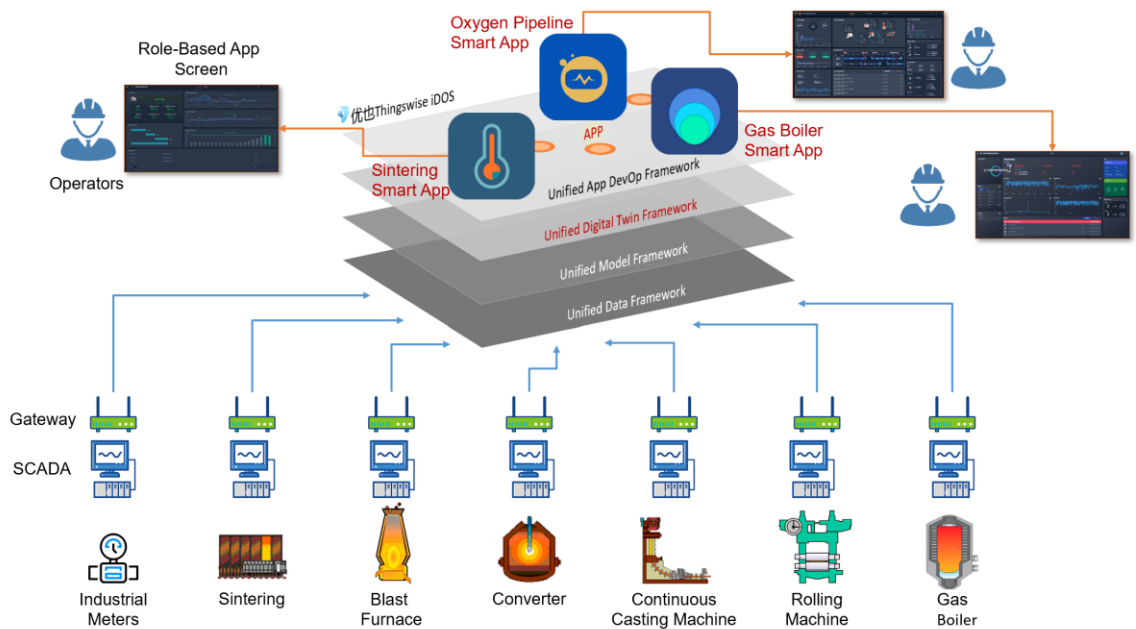


Figure 8: Apps and Platform Deployment Architecture

pipeline smart app seeks optimization across multiple sub-processes (blast furnaces, converters, and continuous rolling and oxygen generation—not shown in the figure).

- The development process of the smart apps involving analytic modeling typically include:
  - Business requirement gathering - identify the operational/business problems (pain points) and understand the requirements for solving these problems;
  - Solution design - determine the output of the analytics required to solve the specific problems, evaluate the input data needed to support the analytics, decide the analytic approach (first-principle, data modeling or a combination of both) and explore and experiment to find the best algorithms;
  - Model development - build and validate the analytic models with data collected from the targeted environments; and
  - Model Tuning - after the model is deployed in the real environment, fine-tune the model with real world data and validate the outputs.

### 7.1 Sintering Smart App

Sintering is an early stage sub-process in the iron-and-steel making process. It fuses iron ore fines (dust) with other fine materials at a high temperature to create sinter, a single

porous mass that can be used in a blast furnace.

**The Problem:** Due to variation in the quality and thickness of mineral materials, as well as equipment operational conditions, there is a substantial percentage of sinter with terminal temperature that does not meet quality requirements, requiring re-processing—resulting in additional costs from energy, time and labor.

**The Solution:** Gather temperature and pressure data for various wind boxes, along with qualitative data about the attributes (such as moisture of the material and thickness of the mineral materials on the trolley where these data are available). Next, predict the terminal temperature of the sinter and provide operational recommendations to the operator to adjust the speed of the trolley to avoid over-burning or under-burning the sintered ore to ensure optimal quality.

### 7.2 Gas Boiler Smart App

Gas boiler is not a primary sub-process in the iron-and-steel making process but a necessary supportive sub-process that consumes the surplus blast furnace gas to generate electricity to be supplemented in the other sub-processes.

**The Problem:** Boilers, especially self-maintained power plant boilers such as those deployed in iron-and-steel plants, face large variations in fuel quality and supply, as well as large fluctuations in operating load. After a few years of operation, its thermal efficiency declines, falling below the design value and resulting in increased operating cost. It has been challenging to evaluate

online thermal efficiency, not because of the complexity of calculation but rather because of the unavailability of online data which are usually scattered across multiple data silos and hard to access. Without online evaluation of the thermal efficiency, it is impossible to optimize the boiler's operation.

**The Solution:** Gather all the relevant design parameters, historic performance data, operating state data (load, gas consumption, oxygen concentration, outlet carbon concentration, temperature values at air inlet, boiler surface, smoke exhaust, water inlet, steam outlet and other dozens of parameters), perform online thermal efficiency calculation, assess potential optimization opportunities under the operating conditions and provide specific operational recommendations (such as increasing or decreasing inlet air flow to ensure optimal thermal efficiency).

### 7.3 Oxygen Pipeline Smart App

In an iron-and-steel plant, various sub-processes including blast furnace, converter and continuous casting use a large amount of oxygen gas. The gas is typically supplied by oxygen production equipment with limited capacity.

**The Problem:** The oxygen-consuming equipment run at different production paces and rhythms. For example, a blast furnace is largely run continuously while converters run in a batch production process. The total consumption of oxygen is thus not in a steady state; rather, it often comes with peaks and valleys in the amount required to maintain smooth production across all these sub-processes. This can lead to oxygen shortages at times which cause production

stoppage for some sub-processes (e.g. converters) and oversupply at other times which, at its worst, can result in wasteful discharge into the atmosphere.

**The Solution:** Gather production scheduling and operational data from all relevant sub-processes; predict the amount of oxygen consumption in the pipeline while accounting for the oxygen consumption priorities among the sub-processes; and provide specific operational recommendations to the operators at various sub-processes to fine tune production scheduling and oxygen consumption levels where appropriate. The operational recommendations are given to maintain a balance of oxygen demand and supply and to steady oxygen pressure in the pipeline while maximizing productivity.

### 7.4 Learnings

Aiming to solve real-world problems in an iron-and-steel plant, we have deployed a number of smart apps with an Industrial Internet platform implementing a digital twin framework. This deployment is still in the early stages, and its full value will be evaluated in the coming months. However, we have garnered some learnings through this deployment so far:

- Deep knowledge of operational/production processes is required to understand what the customers' needs (pain-points) are and where optimizations are most valuable and feasible (low-hanging fruits).
- To be successful in realizing the benefit of these smart apps, committed customers are needed—not only for

financing the projects but also for a strong willingness to adapt their workflows to the new tools and train their operators to use them.

- After the initial installation of the smart apps, continuous efforts to collaborate with customers are needed to increase the accuracy of the models and gather new requirements to improve the apps.
- OT and IT convergence is not only in the customer environment but also in house; OT experts, Data Analytic experts and App developers (IT) need to collaborate seamlessly in order to deliver quality products.
- Collecting and validating data from the large number of equipment, meters and

sensors are still the most daunting tasks in the implementation.

- We have proved that it is feasible to deploy an Industrial Internet platform with a digital twin framework in a manufacturing environment. We have also proved that such a platform greatly simplifies the implementation of data-driven smart apps. It provides a solid foundation for adding new data-driven smart apps for continuous optimization of production processes.

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