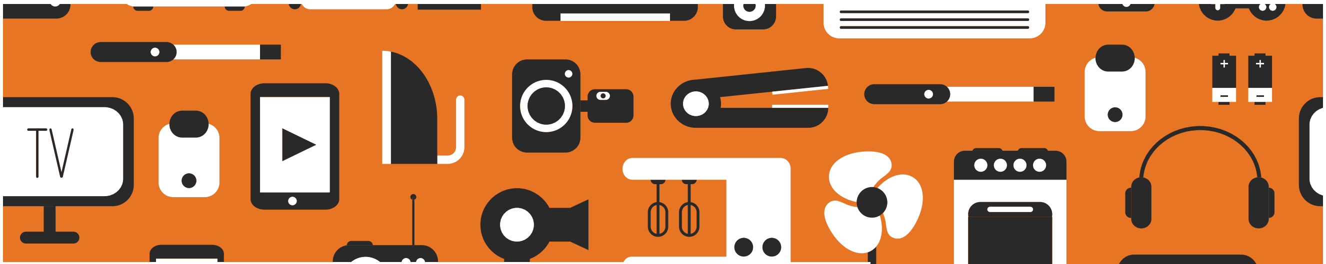

Industry 4.0 and Digital Twins

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Digital twin analytics brought a new dimension to the Industrial Internet of Things. This article will discuss its contribution toward increasing productivity for small and midsize enterprises by reducing production downtime through prognostics and health management strategies.

Factories have evolved through four industrial revolutions. The first factory in the United States was a textile manufacturer in 1790. This factory joined the first industrial revolution (I-1.0), which included mechanization. This was marked by product creation transitioning from handcraft to machines that were driven by waterwheels or steam engines. The second industrial revolution (I-2.0) began with electrification and the introduction of mass production. The third industrial revolution (I-3.0) ushered in digital electronics, automation, and the Internet. We are now in the fourth industrial revolution—referred to as *Industry 4.0* (*I-4.0*). I-4.0 began in the early 2000s with autonomous robotics, artificial intelligence, and cyberphysical systems. Part of this evolution included the connectivity provided by the Internet of Things (IoT) to share data between equipment. I-4.0 continues to evolve with factories improving their manufacturing processes while integrating the latest technologies, often called *smart manufacturing*.

The IoT has been around for decades, connecting many measurement devices and control systems. The IoT has been integrated into many domains, such as education, health care, agriculture, cities, and manufacturing. The IoT within the manufacturing domain is referred to as the *Industrial IoT* (*IIoT*). The IIoT leverages networking sensors, instruments, and devices to enhance the manufacturing process. The IIoT has benefited from IoT innovations to improve operations such as the manufacturing system maintenance process. In this article, we will explore how the IIoT has contributed toward the predictive maintenance of manufacturing systems using digital twin technology, an application in smart manufacturing.

Although the IoT has had many inconsistent definitions over the years, the foundational elements, called *primitives*, of the IoT remain the same in all IoT applications.[1] As described in a National Institute of Standards and Technology (NIST) special publication,[2] there are five

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IoT primitives: a sensor to measure physical properties, aggregator software to transform collected data, a communication channel to transmit the data, an external utility to execute processes and store data, and a decision trigger to command an actuator. These primitives are the building blocks that perform network actions and the framework around sensor data analytics. IIoT scenarios, typically called *use cases*, perform analytics to transform data into information for the purposes of authentication, encryption, and reliability in the manufacturing domain.

An IIoT system contains the IoT building blocks within a distributed architectural system composed of components located on networked computers. These components contain numerous sensory devices, and the data are collected from those sensors and analyzed to communicate signals that coordinate the manufacturing actions.

An IIoT system generates large amounts of data from instrumentation and sensors during the manufacturing process. Cloud technology collects, stores, and analyzes these big data of measurements to be mined. As more manufacturing elements get connected to share data, a digital equivalent of the machinery is useful to optimize a production process—this digital equivalent is called a *digital twin*. Digital twins use information to simulate the manufacturing process in a virtual space for the validation of physical machinery.

APPLICATION OF THE IIoT FOR SMART MANUFACTURING

Elon Musk has stated that "the factory is the machine that builds the machine" and is "100 times" more challenging than building a car. The two main challenges in effectively running a factory are operating at a profit and maintaining the reliability of the plant's machinery. A large amount of research has focused on these challenges through three product lifecycle management (PLM) stages: 1) the product is designed; 2) the product is produced; and 3) the product is put into service.

The second PLM stage, product production, is the process that transforms raw material into useful artifacts with the manufacturing steps of cutting, forming, and joining. At the shop-floor level, individual machines are assembled into work cells; specialized work cells are assembled into production lines; and multiple production lines compose the manufacturing factory system. Keeping all these elements functioning harmoniously is where the IIoT adds value because it uses data connectivity to run the operation efficiently. Optimally maintaining production machinery is crucial for enterprise profitability.

Digital twins use information to simulate the manufacturing process in a virtual space for the validation of physical machinery.

A state-of-the-art digital manufacturing platform relies on an IIoT for configurable data collection, data interoperability, configurable data analytics, and customizable dashboards.[3] These elements, described in more detail next, constitute digital twin technology:

- *Configurable data:* These come from various sources: sensors embedded in the machines, programmable logic controllers, communication protocols, and business information systems.
- *Data collection and interoperability:* Data routing and preprocessing interfaces connect the shop-floor equipment to accept different data formats and to file them in a common repository. A data bus infrastructure is the means to stream events and circulate information to various components. A device registry directs how to access devices and data sources.
- *Data analytics:* A processor engine executes data processing logic based on analytic algorithms. Analytics identify fault patterns and develop decision insights to enable intelligent manufacturing in a complex environment.[4]
- *Dashboards:* An end-user display of figures visualizes the analytic results.

Computer-aided design technologies enable existing modeling and simulation capabilities to evolve into digital twins. Digital twins represent actual products, real processes, or both in a virtual state that can be functionally analyzed for performance.

NIST has defined a digital twin as "the electronic representation—the digital representation—of a real-world entity."[5] A digital twin will exist in a computer software application in practice. A human user will manipulate the digital twin using a visual graphic representation. Representing the real-world entity, static views and dynamic simulations can be used to study the behavior of the digital twin.

To achieve a digital twin's potential, numerous digital twins must operate seamlessly across various manufacturing machinery. Interoperability (to exchange and use information between machines and within systems) can be achieved by adopting communication protocols that allow multiple suppliers to share data. Industry is developing architecture standards to address these implementation challenges. Researchers have combined testbed hardware systems and sandbox software systems to demonstrate and evaluate technologies across suppliers' applications.[6] A digital twin framework is emerging to support system-wide performance monitoring for smart manufacturing processes.

Digital twin implementation is fundamental to smart manufacturing. However, this is especially challenging in small and midsized enterprises. The International Organization for Standardization (ISO) developed ISO 23247, Digital Twin Manufacturing Framework, to provide a standard to support digital twin applications. NIST created three use case scenarios based on the ISO standard:[7]

- *Machine health digital twin:* This scenario uses process and equipment data to monitor, troubleshoot, diagnose, and predict faults and failures in manufacturing equipment.
- *Scheduling and routing digital twin:* This scenario manages manufacturing systems for more flexibility in producing different products using the same resources in response to market demand for more customized products.
- *Virtual commissioning digital twin:* This scenario uses simulation technology to design, test, and evaluate upgraded control systems before connecting them to real equipment.

In general, most large manufacturing enterprises possess adequate resources to engage in all three digital twin use scenarios. Likewise, many midsized manufacturers have sufficient resources to develop machine health and scheduling and routing digital twin use technology. Small manufacturing companies with limited resources for new technology should first deploy machine health digital twin applications.

DIGITAL TWINS AND MACHINE HEALTH: REACTIVE TO PREDICTIVE

Monitoring machine health is a priority for a manufacturing company. Monitoring uses sensors to collect real-time data from measurement devices embedded in the machinery that determine the state of the physical entity's actual performance. Integrating the physical data collected by various sensors throughout the product's lifecycle and virtual data using digital twins can be processed by analytics to result in improved products and processes.

> A digital twin framework is emerging to support system-wide performance monitoring for smart manufacturing processes.

The vision for digital twins is to use real-time data to dynamically update a digital representation that can be viewed and manipulated.[5] The updated digital twin could be used to determine the current state of the health of the machine and to predict through simulation its future health state.

The machine health digital twin uses sensory data from manufacturing equipment to minimize the impact of machine downtime.[7] By collecting key performance indicators in real time, such as spindle speed, feed rates, energy consumption, temperature, and vibration levels, deviations from allowable limits can be identified and resolved to prevent production interruptions. Data visualization trends alert operators to implement control commands to mitigate anomalies. As faults are addressed, the evolving digital twin will enhance its comprehensiveness of the operating environment.

Christou et al.[3] discussed the challenges to implement digital twins in manufacturing. Current implementations are tailored to specific product lines and not generalizable to other manufacturing plants. What industry requires are modular and flexible turnkey solutions. By focusing on I-4.0 smart manufacturing technologies, use cases will increase, such as adopting digital twins for predictive maintenance.

PREDICTIVE MAINTENANCE IMPLEMENTATION OF PROGNOSTICS AND HEALTH MANAGEMENT

Prognostics and health management (PHM), a digital twin application in smart manufacturing, was first used in the aerospace industry to predict aircraft structural life.[8] High-fidelity digital twin-driven PHM overcomes the traditional method's shortcoming of depending on empirical data by using multiphysics simulation to perform fault diagnosis. These advantages are evident in models, data, interaction, and decision making. A practical situation can be more accurately modeled by including the dimensions of geometry, physics, behavior, and rules. Physical data and virtual data are merged with historical data, real-time data, and simulation data in big data analytics. A connection between physical and virtual space yields better control of the physical machinery while upgrading its virtual model. A more rational maintenance strategy will result from digital twin decision-making optimization.

Manufacturers practice one of three distinct maintenance strategies: reactive, preventative, or predictive:[3]

- *Reactive maintenance:* Reactive maintenance repairs the asset when it has already failed, resulting in equipment

breakdowns: for example, changing your car's motor oil only when a dashboard warning light illuminates.
- *Preventive maintenance:* Preventive maintenance is performed at regular intervals to prevent unexpected equipment failures resulting in downtimes: for example, changing your car's motor oil every 5,000 miles or six months, whichever comes first.
- *Predictive maintenance:* Predictive maintenance monitors the performance and condition of an asset to identify the best time to maintain it before it breaks down: for example, changing your car's motor oil when viscosity and contamination sensors indicate that the lubricant has degraded to the minimum threshold of useful life.

Predictive maintenance is a smart manufacturing use case for I-4.0. Predictive maintenance systems use the structured architectures of cloud computing, the IIoT, data analytics, and augmented reality to accomplish their function. Preventative maintenance procedures can be replaced with predictive maintenance practices, as illustrated in Figure 1.

To implement predictive maintenance, there needs to be the integration of multiple data sources, application of machine learning for optimization, and implementation of adaptable digital twins for changing manufacturing production processes. Benefits for the company are improved product quality, reduced production costs, faster times to market, and reduction in scrap.

Smart devices can automatically identify machine anomalies to predict future events. Vibration characteristics' classification can predict anomalies in electric induction motors.[10] Event identification assists maintenance technicians and engineers to predict future problems and act in advance. Accelerometers installed on a motor shaft can measure misalignments and eccentricities. The severity of vibration measurements can be classified according to ISO 2372 ("Mechanical Vibration of Machines With Operating Speeds From 10 to 200 rev/s – Basis for Specifying Evaluation Standards") as good, satisfactory, unsatisfactory, or unacceptable. A supervised learning model that applies past machine learning to new data can automatically classify these vibrations. Rubio et al.[10] successfully detected vibration severity faults demonstrating a cyberphysical system's effectiveness at predictive maintenance.

In another example presented by Nunez and Borsato,[11] a centrifugal pump was monitored using ISO 13379-1 (Failure Modes Symptoms Analysis) techniques and symptoms. This standard ranks the severity of the effect of a failure mode in relation to the required function as catastrophic, critical, marginal, or insignificant. Additional criteria are provided for failure detection, symptom detection, and prognosis sensitivity. A Monitoring Priority Number is generated by the mathematical product of multiplying the four rankings together with a resultant high value indicating a predicted failure mode. The roller bearing that allows the shaft to rotate to transport fluid was the component modeled. Representation of rotating machinery could diagnose failure using vibration analysis for PHM. The classifications for the component were good, satisfactory, alert, or alarm, depending on the accelerometer measurement. Previously, specialists analyzed the operational fitness of the centrifugal pump. This structured ontology implemented PHM for smart manufacturing machinery used digital twin technology. Thus, physical asset managers received warnings about the estimated time to failure and decided when to plan maintenance.

> The vision for digital twins is to use real-time data to dynamically update a digital representation that can be viewed and manipulated.

Maintenance work orders describing routine and unplanned activity are an untapped source of human knowledge.[4] These unstructured records contain information about when a maintenance activity was performed, fault patterns, component lifecycle information, and diagnostic steps performed to resolve

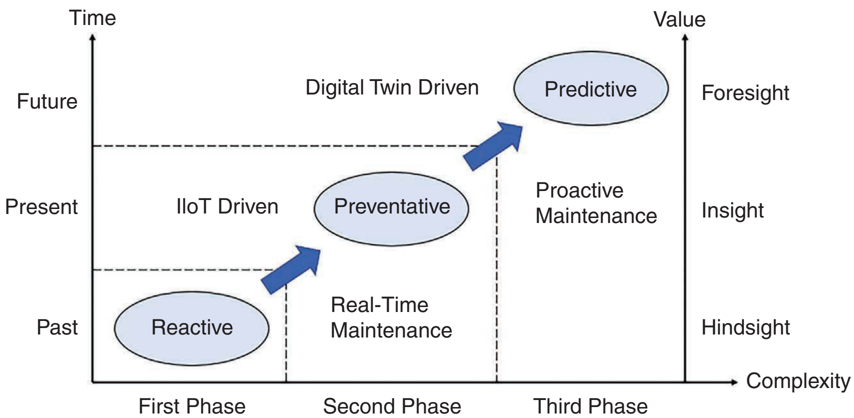

FIGURE 1. The evolution of shop-floor maintenance strategies. (Source: Adapted from Zhuang et al.[9])

faults. Useful insights can be obtained by mining this source of human knowledge from experienced technicians. Digital twins can be used as a prognostic tool to train inexperienced personnel based on an experienced trained operator's approach to solve a legacy maintenance problem.

DIGITAL TWIN BENEFIT FOR SMALL AND MIDSIZED ENTERPRISES

Digital twin technology has the potential to reduce risk, downtime, and energy consumption. Digital twins can improve safety, training, and quality in small and midsized enterprises. Adopting this technology is challenged by plug-and-play interoperability, access to monitoring and control data, the interconnectivity of machinery, and the integration of various equipment.

Profitability in manufacturing is primarily driven by avoiding unplanned downtime. Increased levels of automation within an IIoT architecture improve industrial maintenance management. Smart manufacturing factories use real-time sensory data to gain valuable insights to avoid machinery failures. In addition, digital twin technology along with past maintenance records can improve product design and usage as well as manufacturing processes and maintenance. Operation managers can use these technologies to enhance diagnostic, prognostic, and decision-making practices.

Small manufacturing companies are challenged with implementing digital twins to simulate their operations. Standard procedures for creating digital twin applications are needed to provide precise definitions, common terminology, and implementation guidelines.

Digital twins provide more opportunities to improve manufacturing processes to become smart or intelligent. Future studies should explore how small manufacturing companies can implement digital twins for predictive maintenance of their production processes. An effective digital twin of a factory can economically deploy I-4.0 technologies by integrating instrumentation, network, databases, modeling, analytics, and dashboard elements for enterprises to remain competitive in the marketplace. ◼

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