The Convergence of Digital Twin, IoT, and Machine Learning: Transforming Data into Action

Maninder Jeet Kaur, Ved P. Mishra and Piyush Maheshwari

Abstract Digital twins, Internet of Things (IoT), block chains, and Artificial Intelligence (AI) may redefine our imagination and future vision of globalization. Digital Twin will likely affect most of the enterprises worldwide as it duplicates the physical model for remote monitoring, viewing, and controlling based on the digital format. It is actually the living model of the physical system which continuously adapts to operational changes based on the real-time data from various IoT sensors and devices and forecasts the future of the corresponding physical counterparts with the help of machine learning/artificial intelligence. We have investigated the architecture, applications, and challenges in the implementation of digital twin with IoT capabilities. Some of the major research areas like big data and cloud, data fusion, and security in digital twins have been explored. AI facilitates the development of new models and technology systems in the domain of intelligent manufacturing.

Keywords Digital twins · Internet of things (IoT) · Artificial intelligence (AI) · Machine learning · Big data · Cyber-physical systems (CPS)

1 Introduction

There had been various advancements in new generation information technologies like IoT, AI, big data, cloud computing, edge computing, etc. that have wide applications in smart manufacturing [1]. The advanced computing and analytics in the cyber world has opened a bright perspective to smart manufacturing. The increase in digitization of manufacturing opens up various opportunities. It is predicted by

M. J. Kaur (✉) · V. P. Mishra · P. Maheshwari
Department of Engineering, Dubai International Academic City, Amity University Dubai, Dubai, UAE
e-mail: mkaur@amityuniversity.ae

V. P. Mishra
e-mail: vmishra@amityuniversity.ae

P. Maheshwari
e-mail: pmaheshwari@amityuniversity.ae

M. Farsi et al. (eds.), *Digital Twin Technologies and Smart Cities*, Internet of Things, https://doi.org/10.1007/978-3-030-18732-3_1

Gartner in 2016 that more than 20 billion devices (majority from the manufacturing industry) would be connected to each other by 2020, which further will generate 40 zettabytes of data in raw form as unstructured, semi-structured, and unstructured [2, 3]. Hence, there is a need to organize, analyze, and extract information from this raw data to obtain valuable information with the use of advanced computing mechanisms and algorithms [4, 5].

In conventional approach, the designers use the computer-aided simulation and engineering tools to design and predict the life cycle and perform various physical testing mechanisms. They do optimize design to maximize performance and cut down design cost. But in this approach, there is a limitation on tolerances, strategies relationships amongst the configurations, planning, etc. [6]. However, the development of computing industry with artificial intelligence, faster processing, enhanced algorithms, and increasing computational power in the field of products and production line—digital twin—enable the ability of real-time control and digitization [7–10]. Physical object, process or system can be represented with the help of digital twin. With the combination of data and intelligence that represent the structure, context, and behavior of a physical system, it offers an interface that allows monitoring the past and present operation and makes prediction about the future [11]. Therefore, digital twin, integrate AI, software analytics, and machine learning data to create digital simulation models that update and change as their physical equivalents change. This provides real-time monitoring and updates from multiple sources at the same time. It creates virtual models for physical objects in the digital way to simulate their behavior [12]. The virtual models could understand the state of physical entities through sensing data, to estimate and analyze the dynamic changes. The digital twin would achieve the optimization of the whole production process [13].

This chapter is organized as follows. The concepts and architecture of digital twin is reviewed in Sect. 2. The applications and challenges are also discussed in this section. Section 3 discusses the related work in the area of digital twins. Smart and intelligent manufacturing with AI evolution is explored in Sect. 4, followed by conclusions.

2 Digital Twin—Concept and Architecture

The growth of advanced technologies is paving way for the smart cities, where all the physical objects will have embedded computing and communication capabilities so that they can sense the environment and communicate with each other to provide the services. These intelligent interconnections and interoperability are also termed as IoT or machine-to-machine (M2M) communications [14]. Some of the important domains of a smart city are the smart energy, smart home, smart transport system, and smart manufacturing. Because of the affordability and availability of the sensors and actuators, data acquisition has become relatively easier. Monitoring and diagnosing the manufacturing machines through the Internet is a challenging task. The convergence of the physical and virtual worlds of manufacturing is still one of the major challenges in the field of Cyber-Physical Systems (CPS), which needs more research. To tackle these challenges, Industry 4.0 was conceptualized [15], which mentioned that if the production systems are made intelligent and smart, they can function more efficiently [16, 17]. There have been many developments to enable this, one of which is digital twin [18].

"Digital twin" is a concept that creates a model of a physical asset for predictive maintenance. This model will continually adapt to changes in the environment or operation using real-time sensory data and can forecast the future of the corresponding physical assets [19]. It can monitor and identify potential issues with its real physical counterpart. In addition, it allows the prediction of the remaining useful life (RUL) of the physical twin by leveraging a combination of physics-based models and data-driven analytics. It consists of three main parts: (i) physical products in real space (ii) virtual products in virtual space, and (iii) the connections of data and information that will tie the virtual and real products together. Therefore, collecting and analyzing a large volume of manufacturing data to find the information and connections has become the key to smart manufacturing.

The concept of digital twin presented by Grieves at one of his presentations in 2003 on Product Lifecycle Management (PLM) at University of Michigan [20]. GE has started its digital transformation journey centered on Digital Twin, by building critical jet engine components that predict the business outcomes associated with the remaining life of those components [21].

The work done in [22] was the first initiative to come up with a dynamic Bayesian network approach for digital twin, where they utilized the concept of digital twin for tracking the evolution of time-dependent variables to monitor aircraft structure.

2.1 Architecture

The basic architecture of digital twin consists of the sensor and measurement technologies, Internet of Things, and machine learning. From the computational perspective, the key technology to propel a digital twin is the data and information fusion that facilitates the flow of information from raw sensory data to high-level understanding and insights [23]. The key functionality of digital twin implementation through physics-based models and data-driven analytics is to provide accurate operational pictures of the assets [24]. This helps the digital twin mirror the activities of its corresponding physical twin with the capabilities of early warning, anomaly detection, prediction, and optimization. The IoT system carries out real-time data acquisition through its smart gateway and edge computing devices. The preprocessed online sensory data is fused to feed the digital twin model. The offline data, after processing with text/data mining algorithms and then inputted to the digital twin as well. The offline computing resources utilized to train deep learning models. The digital twin combines modeling and analytics techniques to create a model of a specific target, e.g., flight critical component, etc. Hence, digital twin use is specified as predictive maintenance workflow to enable the delivery of accurate forecasting, using the data that is continuously acquired with IoT sensors via machine learning algorithms.

2.2 Applications of Digital Twin

Digital Twin determines the best course of action by eliminating the guesswork to service the critical assets in the manufacturing units. The increasing adoption of the IoT is ideal for enterprises to leverage digital twin platforms to boost their services and platforms. Some of the applications are given as follows [25]:

- Performance Optimization—Digital twin helps to determine the optimal set of parameters and actions that can help maximize some of the key performance metrics and provide forecasts for long-term planning. For example, NASA proposed and adopted for monitoring and optimization on safety and reliability optimizations of spacecraft [26, 27].
- Healthcare—Digital twin can be used for capturing and visualize a hospital system in order to create a safe environment and test the impact of potential changes on system performances. Not just operations, it also helps to improve the quality of health services delivered to the patients. For example, a surgeon can use it for a digital visualization of the heart, before opening it.
- Improve customer experience—As customers play a key role in influencing the strategies and decisions in any business. Enhancing the customer experience to retain and explore new customer base is the goal for the businesses. By directly creating a digital twin of the customer-facing applications, they can get feedback that boost the services directly offered to the customers.
- Maintenance—Digital twin can analyze performance data collected over time and under different conditions. For example, a racecar engine can be visualized to identify the required maintenance such as the component that is about to burn out.
- Machine Building—Digital twin is also used as a digital copy of the real machine that is created and developed simultaneously. Data from the real machine is loaded into the digital model to enable simulation and testing of ideas even before actual manufacturing starts.
- Smart Cities—Capturing the special and temporal implications to optimize urban sustainability. For example, "Virtual Singapore", a part of the Singapore government's smart nation Singapore initiative, is the world's first digital twin of an existing city-state, providing Singaporeans an effective way to engage in the digital economy and urbanization.

2.3 Challenges of Digital Twin

Some of the challenges to build and implement digital twins are as follows:

– The challenge to build a digital twin model combining product lifecycle management, manufacturing execution system and operations management system [28, 29]. After releasing process plans to the manufacturing execution system, using digital twin model in the cloud server to generate detailed work instructions associated with the production process design. Therefore, if there is any change from a production environment, the entire process is updated accordingly in the design and plan [30].
– Another challenge is how to build a more comprehensive digital-twin-driven physical-cyber-social connected production line [31–33]. The preliminary function of digital twin model is to help enterprises to design and manufacture of excellent products. However, the main aim of a digital twin model is to continue to accumulate knowledge of the design and manufacturing is reused and improved continuously [34].
– One of the most important challenges is to incorporate the big data analytics [35] into digital twin model. When directly collect real-time data from the production equipment, it will cover the information on the digital twin model. When compared to design with actual manufacturing result, the big data analytics are supposed to identify whether there is a difference and find out the cause of the differences [36, 37]. In addition, intelligent decoupling of combined problems is desirable.
– Currently, there are no optimized methods to integrate the different engineering models on the digital twin. There are data transfer mechanisms between domain-specific engineering tools. Besides technical reasons, a cross-domain collaboration also has a challenge of employing modularization methods as a multi-domain mechatronic system as viewed from a physically oriented or a function-oriented perspective [38].

3 Machine Learning, Artificial Intelligence, and IoT to Construct Digital Twins

Digital twin consists of the sensors and measurement technologies, IoT, simulation, and modeling and machine learning technologies. IoT devices are expected to generate a significant amount of data as their use becomes ubiquitous. IoT-cloud communication models and big data generated by devices results in increased latency and incremental data of cloud services and upstream data on behalf of IoT services.

3.1 Related Work

There are various fields, which contribute to the digital twin implementation—networking, cloud/edge computing, machine learning, sensors, etc. In the field of artificial intelligence, work done by [39] were the first one to initialize with a dynamic Bayesian network approach for digital twin, wherein they utilized the concept of digital twin for tracking the evolution of time-dependent variables to monitor aircraft structure.

In IoT world, AI will enhance the functionalities of digital twins in which a dynamic software model is formed of a physical thing or system that relies on sensor data to understand its state, respond to changes, improve operations, and add value. In [13], authors proposed digital-twin-driven product design, manufacturing, and service with big data, but their work has been mostly investigative in nature. Currently, the Industrial Internet or Industrial Internet of Things (IIoT) use digital twins for implementation in manufacturing industry. The work done in [40] discusses how IoT devices and IoT systems can be managed and optimized throughout their lifecycle using the mechanism of digital twins.

In manufacturing, IoT devices generate the data from product lifecycle, such as design, manufacturing, MRO, etc., [41]. Manufacturing data are generally from the following aspects [21]:

- Data from the manufacturing systems, e.g., MES, PDM, SCM, ERP, etc., and from other computer-aided systems like CAD/CAM, CAE, etc.
- Data from Internet/users, e.g., from e-commerce—Amazon, Walmart, Facebook, twitter, etc.
- Data from manufacturing equipment with respect to real-time performance, material of product data, environmental data, etc.

Processing of the collected data should go through various steps to extract the information. As the data collected via various ways like sensors, application-programming interface (API), software development kit (SDK), etc., undergoes cleaning before processing and analyzing [42–44]. This cleaned data integrates and stored for the exchange and sharing for manufacturing data at all levels. Further, the real-time data or offline data analysis and mining by advanced data analysis methods and tools like AI and machine learning, deep learning, etc. utilize cloud computing [45–47]. The valuable information extracted from large number of dynamic and fuzzy data enables manufacturers to deepen their understandings of various stages of product lifecycle. Hence, this helps the manufacturers to make more rational and informed decisions.

In Intelligent manufacturing (IM) area, the first book was published in 1988 [48], which resulted in the emergence of many methods, applications, and techniques in various areas of manufacturing like design, scheduling, production, control, modeling, testing, etc. [49]. In [49], the authors surveyed the relevant AI methods introduced in the field of manufacturing and grouped them as knowledge-based/expert systems, fuzzy logic, multi-agents, neural networks, evolutionary genetic algorithms, and simulated annealing. Introduction of knowledge-based/expert systems efficiently in computer integrated manufacturing (CIM) components but intelligent, manufacturing system (IMS) in industry were mainly in large companies [50]. The most famous IMS research was the international scheme of joint research called Intelligent Manufacturing System found in 1995 that influenced from dated back to 1989 from Japan [51]. In 90's, agent-based systems for intelligent manufacturing were developed followed by the web service-based systems for manufacturing and crowdsourcing [52–55]. The agent-method seemed to be the potential solution as it offered a proper paradigm for the intelligent CIM components and IMS [56–58]. Intelligent agents are used in distributed AI and such an agent-based approach can handle the issues of the present software applications, specifically those working conditions that are highly dynamic and uncertain [59]. However, most agent-based systems are still at a research and prototype stage in labs and not widely adopted in manufacturing.

4 Intelligent and Smart Manufacturing with AI Evolution

Some of the key research areas, which we have studied in this chapter, are *Fusion of Big Data, Cloud and Cyber-Physical Systems, Information and Data Fusion in Decision-Making, Security in Digital Twins/Smart Manufacturing.*

4.1 Fusion of Big Data, Cloud and Cyber-Physical Systems

The cyber-physical systems (CPS) is another name for digital twin phenomena that makes possible the data analysis based control of the resources or physical environments with much ease. Here, the physical systems collect sensory information from the real world and send them to the digital twin computational modules through communication technologies (wireless). It is challenging to incorporate big data analytics into CPS [60]. The technologies used for the implementation of smart manufacturing span a wide spectrum of domains, which are initially referred to as the IoT technologies, and then many other related techniques such as the Internet of services (IoS), CPS, big data, and advanced robotics [61] have been a part. The rise of IoT/CPS and small objects (phones) has made the products more connected and accessible, from which the wealth of data generated allows accurate targeting and further enabling proactive management of enterprises through informed, timely in-depth decision execution [62]. Therefore, the fusion of human, data and smart and intelligent algorithms has far-reaching effects on manufacturing efficiency.

Collection, visualization, and analysis of the large volume of manufacturing data is the key to smart manufacturing. From the input of raw material to the output of finished products, the digital twin manages and optimizes the complete manufacturing process [63]. The virtual workshop or factory include the geometrical or physical models of operators, material, equipment, tools, environment, etc., as well as the behaviors, rules, dynamics, and many other factors [64]. The virtual model of product is created to establish the product digital twin. The product digital twin would always keep in company with the product to provide the value-added services [65]. Some of these are given as follows [66]:

- The product in use is monitored in real-time, as the product digital twin continuously records the product usage status, environmental data, operating parameters, etc.
- The virtual model can simulate the operation conditions of the product in different environments. Hence, it can confirm what effects the different environmental parameters and operation behaviors would have on health, lifetime, and performance to control the status and behavior of the physical product.
- Based on real-time data from the physical product and historical data, the product digital twin predicts the product remaining life, faults, etc.

Based on the predictions for health condition, remaining life and faults, the proactive maintenance is carried out to avoid the sudden downtime. In addition, when the faults occur with the high fidelity virtual model of the product, the fault would be visually diagnosed and analyzed, so that the position of the faulty part and the root cause of fault displayed to the users [67]. These operations–maintenance and repair operations (MRO) which include disassembly sequence, spare parts, etc. provide sustainability. Before starting the actual MRO, the walkthrough about MRO strategies executed in the virtual world based in the virtual reality and augmented reality to impose predictive analysis. As the virtual models faithfully reflect the mechanical structure of the parts and the coupling between each other, it can identify whether the MRO strategies are effective, executable and optimal. The data from the different stage of product lifecycle are accumulated and inherited to contribute to the innovation of the next generation product.

Moreover, in the design phase, product innovation relies on the accurate interpretation of market preferences and customer demands, in accordance with the optimal planning. Besides, once the design changes, the manufacturing process can be easily updated, including updating the bill of materials, processes, and assigning new resources. As a result, the convergence of digital twin, big data and service, enables the production, planning, optimizing and manufacturing process in real-time. In the daily operation and MRO of the product, the virtual models of physical products synchronize with the real state of the product through sensors. The operation status of the product and the health status of the components generated in real-time. In addition to the sensors data, digital twin also integrates the historical data, e.g., maintenance records, energy consumption, etc. and through the analysis of this data, product digital twin can continuously predict the state of the product and remaining life of the product and probability of faults. It can also analyze the unknown problems by comparing the actual product response and anticipating the product response in specific scenarios. Hence, it improves product life and maintenance efficiency and reduces the maintenance cost. Big data analytics is responsible for all the data acquired and analyzed by the smart manufacturing. Therefore, the convergence of the digital twin and the big data is very important for smart manufacturing [13].

4.2 Information and Data Fusion for Decision-Making

More generally, the definition of information fusion is "*the study of efficient methods for automatically or semiautomatically transforming information from different sources and different points in time into a representation that provides effective support for human or automated decision-making.*" [68]. Decision-making in big data is driven by predictions—learning from data (experience) to predict, and actions are taken in response to predictions [69]. Machine learning, which learns from data and uses statistical approaches to assist decision-making that operates well in practice, contrasts with the older expert system approach that aims to mimic the rules from human experts with the help of programmers translating the explicit rules into software code. Digital twin integrates the various data originating from the physical, cyber, and social spaces through information and data fusion techniques to provide human-understandable abstractions and inferences.

Data fusion with the multimodal data collected from heterogeneous data sources, advanced mining techniques may be necessary to fuse the data. The data collected may be in different scales of measurement [70]. This information and data fusion layer consists of various statistical or logic-based methods to integrate the outputs from the data processing layer to achieve a cohesive view of applications. The fusion techniques ensure that there is a combination of computers, smart devices, and people working together. Some of these techniques are given as follows [71]:

- Semantic Reasoning—Semantic web-based methods have been used to map proprietary relational datasets, environment monitoring data streams and participatory sensing data and this data then is combined (with match filters) with user preferences to form a dynamic social structure of things.
- Tensor Decomposition—The tensor-based methods exploit existing approaches for data fusion that can detect hidden information. This method is generally to analyze the behavior similarity of users. Group-centric data fusion is performed based on the approximate tensor, with each element in the approximate tensor representing the prevalence of the corresponding behavior in the group [72].
- Cross-space data fusion through correlation—Cross-space data fusion has taken the form of statistical methods, to calculate correlation between numerical data streams derived from the physical and social space. These include utilizing the data generated by citizens in social networking platforms in conjunction with data from sensor installations to build a model of the city's dynamics.

Decision support mechanisms consists of prediction algorithms that support further insights through data fusion. The flow of information from raw data to high-level decision-making propels by sensor-to-sensor, sensor-to-model, and model-to-model fusion. Therefore, manufacturers will make more rational, responsive, and informed decisions and enhance their competitiveness.

4.3 Security in Digital Twin

Bringing the Internet to the manufacturing industry offers opportunities but also new challenges. The required information flow across many communication networks raises questions about IT and data security that was not relevant when the machines were not programmable and were not connected to any other infrastructure except the power. Therefore, providing security or maintaining the security in the current manufacturing system in organizations are becoming a challenging task due to the cyberattacks and intrusions in current scenario. The security required for the manufacturing system for the following five levels as depicted in the CIM model [73]. CIM is a highly integrated model that has been used and incorporated into many models and standards in the manufacturing industry.

1. Enterprise/Corporate Level—At this level, the decisions related to operational management which define the work flows to produce the end product are made.
2. Plant Management Level—This level manages the decisions locally on the plant management network.
3. Supervisory Level—This level manages various manufacturing cells, each performing a different manufacturing process.
4. Cell Control Level—At this level, processes perform different actions.
5. Sensor Actuator Level—Here, the sensors, actuators, controllers integrate to perform the physical process.

Because of its design, this model is vulnerable to security attacks. The various protocols used to support this infrastructure—modbus, distributed network protocol (DNP3), industrial Ethernet, PROFIBUS, building automation and control networking (BACnet), etc. are only used for supervisory and control mechanisms but not security and lack mechanisms to provide authentication, integrity, freshness of the data, non-repudiation, confidentiality and measures to detect faults and abnormal behavior. Following are the cyber liabilities for most of the manufactures [74]: interruption in business, data breach, cyber extortion, intellectual property, third party damage.

Various solutions to counter these security discrepancies are:

- Public Key Infrastructure—To use device certificates and public key infrastructure (PKI) architectures. Implementing PKI into embedded systems secures the communication layer, creating a system that verifies the authenticity, configuration, and integrity of connected devices. This makes PKI ideal for large-scale security deployments that require a high level of security with minimal impact on performance [73].
- Encryption of the data—Highly confidential data must be encrypted to ensure that only authorized users have access by deploying anti-malware and hardening software on all IT and OT systems. In addition, use of symmetric encryption algorithms, hybrid encryption schemes, cryptographic hash functions, digital signatures, key agreement and distribution protocols are widely used to ensure only

authorized entities. The work done in [75, 76] proposes key management systems are studied and discussed.

- Intrusion detection systems—It is always necessary to monitor the dynamic behavior of the security systems and seek to find if there is an abnormal activity. Intrusion detection system (IDS) approaches tackle these issues. IDS are classified by source of data (audit source)—also called *network based* or *host based* and detection technique (the data needed for analysis)—also called *knowledge-based* or *behavior based*. Receiver operating characteristics (ROC) curve, which depicts the detection probability versus false alarm probability, evaluates the performance of IDS. Studies [77–79] show that most work in this area has been in behavior-based network intrusion systems since knowledge-based systems require detailed knowledge of previous exploits to define characteristics of the attack. Hence, IDS research for smart manufacturing and IoT systems is still in progress and face a lot of challenges due to limited testbed availability and insufficient data from real incidents.
- Policies and Regulations—There are various special guidelines to enforce security mechanisms in smart manufacturing systems [74]. Some of these guides are Guide to Industrial Control Systems (ICS) for SCADA systems, The National Institute of Standards and Technology (NIST), Distributed Control Systems (DCS), Department of Homeland Security (DHS), The Centre for the Protection of National Infrastructure (CPNI), etc.

Planning for security involves understanding the nature of threats, identifying vulnerabilities, quantifying the value to be lost if in case security breach happens and investing in security appropriately. This gives an autonomous model in which products and machines will become active participants in IoT behaving as autonomous agents throughout the production line.

5 Conclusion

Digital Twin has been recognized by many developed companies like GE, IBM, and Cisco as next-generation core infrastructure and are focusing more on developing CPS-related technologies and utilization of platforms. IoT and Artificial Intelligence in smart manufacturing was the initial step to recognize the sensors prerequisite into the machine parts from where the real-time analytics will get the data. Fusion of human, data and smart/intelligent algorithms has far-reaching effects on manufacturing efficiency. However, the intensive communication and high amounts of data involved also bring in new challenges. In this chapter, we discussed the architecture of the CPS, applications, and challenges involved in the implementation of Digital Twins. It also discusses the related work in the area of machine learning, artificial intelligence in the field of smart manufacturing. Furthermore, the key research areas—Fusion of Big Data, Cloud and Cyber-physical systems, Information and Data

Fusion for decision-making and Security in Digital Twins/Smart manufacturing were discussed.

We have discussed the connection between the data about the physical product and the information contained in the virtual product and its synchronization. By merging the virtual product information as to how the product manufacturing takes place, we can have an instantaneous and simultaneous perspective on how the manufactured product is meeting its design specification goals. Hence, information on product manufacturing is predicted and working in real-time as well is monitored. From the security point of view, the potential consequences of security attacks on smart manufacturing systems like, injuries, death, and damage to physical infrastructure, equipment, and the environment are likely to occur simply because the actuators in manufacturing system have connection to such things. It is important that the adoption of IoT and machine learning embed security from the start, integrated with functionality in smart manufacturing systems. Therefore, the convergence of IoT and Machine Learning with Digital twins will improve productivity, uniformity, and quality of the products.

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