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Review

Digital Twin-driven smart manufacturing: Connotation, reference model, applications and research issues

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ABSTRACT

This paper reviews the recent development of Digital Twin technologies in manufacturing systems and processes, to analyze the connotation, application scenarios, and research issues of Digital Twin-driven smart manufacturing in the context of Industry 4.0. To understand Digital Twin and its future potential in manufacturing, we summarized the definition and state-of-the-art development outcomes of Digital Twin. Existing technologies for developing a Digital Twin for smart manufacturing are reviewed under a Digital Twin reference model to systematize the development methodology for Digital Twin. Representative applications are reviewed with a focus on the alignment with the proposed reference model. Outstanding research issues of developing Digital Twins for smart manufacturing are identified at the end of the paper.

1. Introduction

Digital Twin has gained significant impetus as a breakthrough technological development that has the potential to transform the landscape of manufacturing today and tomorrow [1]. Digital Twin [2], acting as a mirror of the real world, provides a means of simulating, predicting and optimizing physical manufacturing systems and processes. Using Digital Twin, together with intelligent algorithms, organizations can achieve data-driven operation monitoring and optimization [3], develop innovative product and services [4], and diversify value creation and business models [5].

Though studies have reported the potential application scenarios of Digital Twin in manufacturing, we identified that current approaches to the implementation of Digital Twin in manufacturing lack a thorough understanding of Digital Twin concept, framework, and development methods, which impedes the development of genuine Digital Twin applications for smart manufacturing. In this study, we discussed the connotations of Digital Twin-driven smart manufacturing in the context of Industry 4.0. The objectives and the contributions of this paper are to provide comprehensive discussions on the impact, reference model, application scenarios and research issues of Digital Twin for achieving smart manufacturing.

The remainder of the paper starts with tracing the vision of Digital Twin and the development to date based on studies from the literature (see Section 2). This is followed by an in-depth discussion on the connotation of Digital Twin-driven smart manufacturing in Section 3, highlighting how Digital Twin will transform the future manufacturing landscape. Section 4 details a Digital Twin reference model and enabling technologies for developing a Digital Twin-driven smart manufacturing solution. An overview of existing Digital Twin applications and some typical application scenarios are presented in Section 5. Section 6 discusses the critical research issues for future research. Section 7 concludes the research work.

2. Digital Twin overview

This section traces the history of the Digital Twin concept, clarifies its relations with several other tropical concepts in the manufacturing domain, summarizes its research and development progress, and highlights the research gaps.

2.1. Definition

Digital Twin was conceived in [6] as a method to predict the structural behavior of an aircraft by analyzing and simulating the aircraft's behavior on its digital model in 2011. A year later, NASA defined Digital Twin as "an integrated multi-physics, multi-scale, probabilistic simulation of a vehicle or system that uses the best available physical

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models, sensor updates, fleet history, and so forth, to mirror the life of its flying twin [2].” There was limited exploration since then, until 2015, the explosion of machine learning, wireless communication and cloud computing boosted the research activities on Digital Twin. Several definitions of Digital Twin came out afterwards. For instance, Digital Twin was seen as the next generation of simulation [7]. Tao and Zhang believed that Digital Twin is a method of achieving the convergence between physical and virtual spaces [8].

Now, Digital Twin has evolved into a broader concept that refers to a virtual representation of manufacturing elements such as personnel, products, assets and process definitions, a living model that continuously updates and changes as the physical counterpart changes to represent status, working conditions, product geometries and resource states in a synchronous manner [9]. The digital representation provides both the elements and the dynamics of how a physical ‘thing’ operates and lives throughout its life cycle.

2.2. Concept clarification

There exist diverse viewpoints on the relationships between Digital Twin and other concepts, such as simulation, Cyber-physical Systems (CPSs) and Internet of Things (IoT). Though these concepts are closely related, they, by their nature, are different on the concept, core elements, and application.

2.2.1. Digital Twin and simulation

A Digital Twin is a digital replica of a real-world ‘thing.’ While this looks close to simulation, Digital Twin is much more. A Digital Twin is a high-fidelity representation of the operational dynamics of its physical counterpart, enabled by near real-time synchronization between the cyberspace and physical space [10]. The operational dynamics are critical elements of a Digital Twin because a twin's behavior is based on near real-time data coming from the actual physical counterpart. Simulation focuses on what could happen in the real world (*what-if* scenario), but not what is currently happening. In the manufacturing context, a Digital Twin can be used for monitoring, control, diagnostics, and prediction, other than just simulation [10].

2.2.2. Digital Twin, CPS, and IoT

Though Digital Twin, CPS, and IoT all use networking and sensors, Digital Twin is a different but interrelated concept with CPS or IoT, as shown in Fig. 1.

A CPS is characterized by a physical asset and its Digital Twin. In contrast, a Digital Twin is limited to the digital model, not the twinning physical asset, though a Digital Twin cannot live without its twining asset in the physical space. In other words, Digital Twin represents the prerequisite for the development of a CPS [12].

IoT refers to connections between a network of physical assets through which data can flow between themselves. The connections are made possible by the secure implementation of computer networks, the Internet, and communication protocols. However, despite the connectivity, IoT does not include the idea of digital models in the cyberspace. The IoT is the infrastructure in the physical space for connecting physical assets [11].

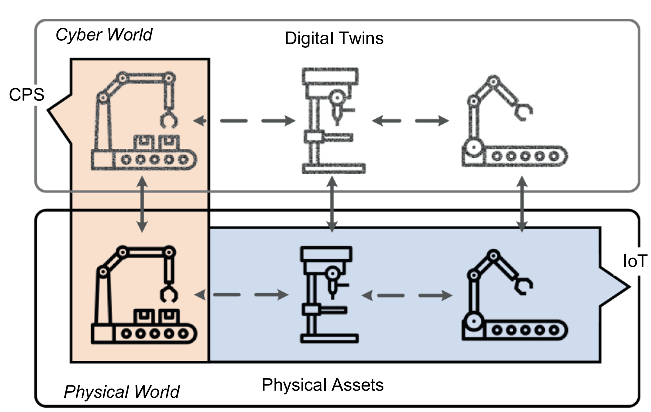

Fig. 1. The relationship between Digital Twin, CPS and IoT (adapted from [11]).

2.3. Research activities

The research activities on Digital Twin have gained hyper growth during the past three years driven by the strategic implementation of Industry 4.0 from world-leading research organizations and tech giants.

2.3.1. Academic research outcomes

Digital Twin related engineering research is in its infancy with significant growth during the past three years as shown in Fig. 2(a). The number of publications on this topic in 2018 tripled that in 2017. A large percentage of the research outcomes come from the US, Germany, and China, who are leading the race to Industry 4.0. A small number of researchers and research organizations contributed nearly 40% of the total number of articles on this topic.

2.3.2. Industry research outcomes

Digital Twin has attracted strong interests from industry practitioners too. The Digital Twin market is forecasted to reach $15.66 billion by 2023 at an annual growth rate of 37.87% according to a market research in 2017 [13]. GE developed a Digital Twin platform – PREDIX that can better understand and predict asset performance [14]. SIEMENS's focus covers smart operations during the complete process of product design, production and operation [15]. ABB emphasizes on enabling data-driven decision makings [16]. Microsoft also geared up its Digital Twin product portfolio, providing a ubiquitous IoT platform for modeling and analyzing the interactions between people, spaces, and devices [17]. Initiatives from these tech leaders have significantly pushed the boundary of Digital Twin for engineering applications.

2.4. Research challenges

Though some early adopters have demonstrated some applications of Digital Twin for manufacturing, current implementation limitations are (1) inadequate understanding of the connotation of Digital Twin-driven smart manufacturing, with the current focus mostly on product operation and maintenance, (2) the lack of reference models for Digital Twin, and (3) superficial knowledge of the research questions and challenges of Digital Twin, with current research outcomes mostly showing preliminary application examples.

The sustainable development of Digital Twin-driven smart manufacturing needs critical analysis on the above aspects based on the development trend of smart manufacturing, which the research in this paper aims to address.

3. Digital Twin-driven smart manufacturing

Manufacturing is becoming smart at all levels from the physical device, through factory management, to production networks, gaining abilities to learn, configure and execute with cognitive intelligence. This section outlines the trend of smart manufacturing and discusses the connotation of Digital Twin-driven smart manufacturing, highlighting the impact that Digital Twin may have for future manufacturing.

3.1. Smart manufacturing

Smart manufacturing is coined by several agencies, such as the Department of Energy (DoE) and the National Institute of Standards and Technology (NIST) in the United States. According to Davis et al., smart manufacturing is the dramatically intensified application of

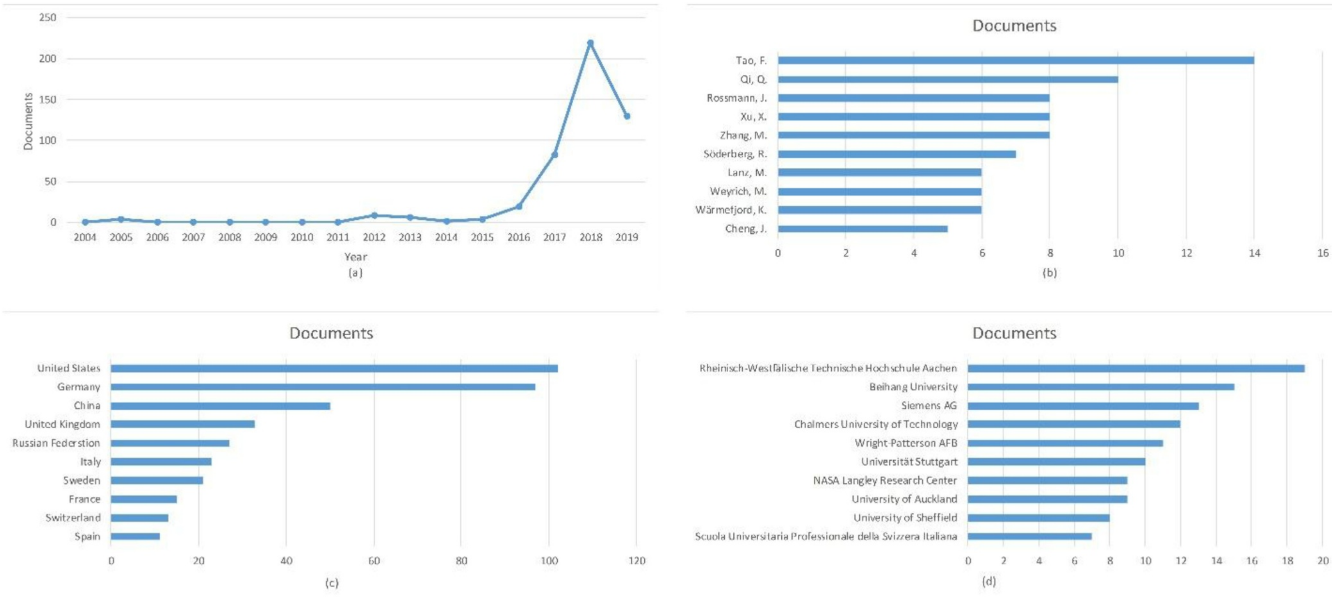

Fig. 2. Statistics from Scopus database (TITLE-ABS-KEY ("digital twin") AND (LIMIT-TO (SUBJAERA, "ENGI")), Date: 2 July 2019). (a) Document per year; (b) Documents by author; (c) Documents by country/territory; (d) Documents by affiliation.

'manufacturing intelligence' throughout the manufacturing and supply chain enterprise [18]. It comprises the real-time understanding, reasoning, planning and management of all aspects of manufacturing processes, facilitated by the pervasive use of advanced sensor-based data analytics, modeling, and simulation. NIST defines smart manufacturing systems as "*fully-integrated, collaborative manufacturing systems that respond in real time to meet changing demands and conditions in the factory, in the supply network, and customer needs.* [19]"

In smart manufacturing, a physical 'thing' in a factory is connected to the Industrial Internet via standard cyber gateways and abstracted as a Digital Twin in the cyberspace. Each Digital Twin in the cyberspace is an abstraction of its counterpart in the physical world by reflecting its physical status. The cyberspace stores and processes the streamed data from connected physical objects. These data are used to model, simulate and predict the status of each physical thing under dynamic working conditions. The pervasive use of smart technologies, such as Big Data Processing and Artificial Intelligence enables the extraction of manufacturing intelligence at every single moment of manufacturing activities. The collective intelligence in locally connected factories and the cyberspace paves the way for some dramatic changes from the aspects of intra-business operation, inter-business collaboration and production model, as shown in Fig. 3.

- **Smart Production**: Manufacturing systems augmented with cognitive intelligence [20] can take over more and more production jobs. Connected and self-organizing manufacturing systems will tackle new manufacturing tasks with high efficiency and flexibility. The relationship between humans and machines will also change; one direction is a factory will become fully-immersed human-machine collaboration space [21].
- **Smart Production Network**: Connected cyber-physical production systems will form a global production network that can respond in almost real-time to dynamic changes in local production systems and external supply chain [22]. A production network of adaptive and self-optimizing production systems can enable autonomous configuration and planning of production activities for production jobs at changing scales to achieve sound economic, environmental and social impacts.
- **Mass Personalization**: Production model will move from a push-type mass production model to pull-type mass personalization [23]. Smart factories that are fully responsive to changes and demands from the factory, supply chain, and customer side can achieve batch-size-of-1 production with high efficiency and flexibility. The ubiquitous manufacturing intelligence in distributed factories and production systems can sense, configure and collaborate by themselves based on near real-time production status and demands, which therefore provides the required agility for producing highly personalized products.

3.2. Digital Twin for smart manufacturing

Digital Twin plays a pivot role in the vision of smart manufacturing. It enables the shift from analyzing the past to predicting the future. The live representation of reality via Digital Twins allows us to evolve from ex-post data gathering and analytics towards real-time and ex-ante business practices. Mirroring the vision of smart manufacturing in Fig. 3, Digital Twin can influence future manufacturing from the following aspects.

- **Digital Twin for manufacturing assets**: A manufacturing asset can be connected and abstracted to the cyberspace via its Digital Twin. Manufacturers can gain a clearer picture of real-world performance and operating conditions of a manufacturing asset via near real-time data captured from the asset and make proactive optimal operation decisions. With truthful information flowing from a manufacturing asset, manufacturers can improve their situational awareness and enhance operation resilience and flexibility, especially in the context of mass personalization.
- **Digital Twin for people**: Digital Twins can also connect workers at the shop floor. The representation of a person, including personal data like weight, health data, activity data, and emotional status can help to establish models to understand personal wellbeing and working conditions of humans in a factory. The understanding of human state at workforce can help design human-centered human-machine collaboration strategies to increase the physical and psychological health of workers, as well as achieving best production performance. Workers can also upskill themselves via ultra-realistic training programs which blend physical factory setups with virtual what-if scenarios. The ability to set up personalized virtual training programs based on Digital Twins of workers and factories can lead

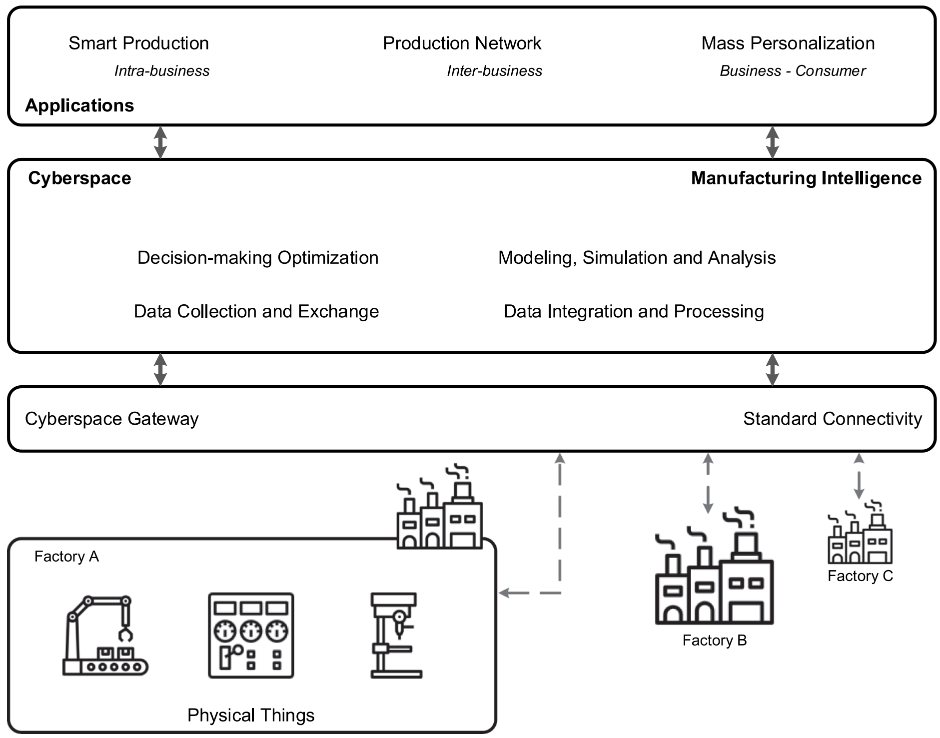

Fig. 3. Smart manufacturing vision.

to tremendous resource optimization and operational efficiency.

- **Digital Twin for factories**: Digital Twins can also work for factories, making a replica of a live factory environment. Digital Twin and data-driven production operations can allow the establishment of a self-organizing factory environment with complete operational visibility and flexibility. Connectivity and data tracking throughout the complete manufacturing process enable factory operations to be transformed into data-driven evidence-based practices, offering the capabilities of tracing product fault sources, analyzing production efficient bottlenecks and predicting future resource requirements.
- **Digital Twin for production networks**: By connecting manufacturing assets, people and service via Digital Twin, every aspect of business can be virtually represented. Connecting distributed Digital Twins between companies will allow companies to build virtually connected production networks. Leveraging Big Data capabilities, this strategy provides unprecedented visibility into operation performance and creates the possibility of predicting future needs in a network of Digital Twins.

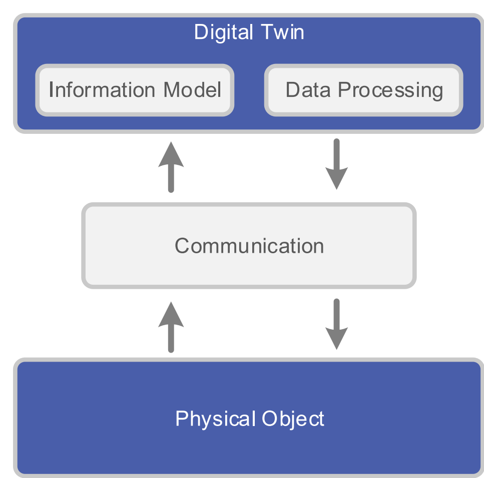

Fig. 4. A Digital Twin reference model.

4. Digital Twin reference model

Digital Twin reflects the two-way dynamic mapping between a physical object and its virtual model in the cyberspace [24]. A Digital Twin presents a middleware architecture that abstracts its physical counterpart for high-level engineering management systems to make near real-time decisions [25]. Fig. 4 shows a Digital Twin reference model. At the technical core, the development of Digital Twin needs three components: (1) an information model that abstracts the specifications of a physical object, (2) a communication mechanism that transfers bi-directional data between a Digital Twin and its physical counterpart, and (3) a data processing module that can extract information from heterogeneous multi-source data to construct the live representation of a physical object. These three components must work together for constructing a Digital Twin. Without an information model to abstract the features of a physical entity, data transmitted to the cyberspace will lose its meaning and context. Without a data synchronization mechanism between a physical model and its information model, the connection and reflection between these two ends will disconnect, and the information model becomes a one-off snapshot of its physical counterpart. High-performance data processing is the key to bridge the gap between the heterogeneous data stream and the Digital Twin information model.

4.1. Information model

A physical object is abstracted with a pre-defined information model that represents its specifications of concern. Standard plays a critical role in providing the information model for describing various physical objects in the manufacturing domain. Fig. 5 lists well-recognized standards that provide standard information models for describing physical objects in the manufacturing domain. These information models are classified into two subtypes: information models for product Digital Twin and information models for production Digital Twin.

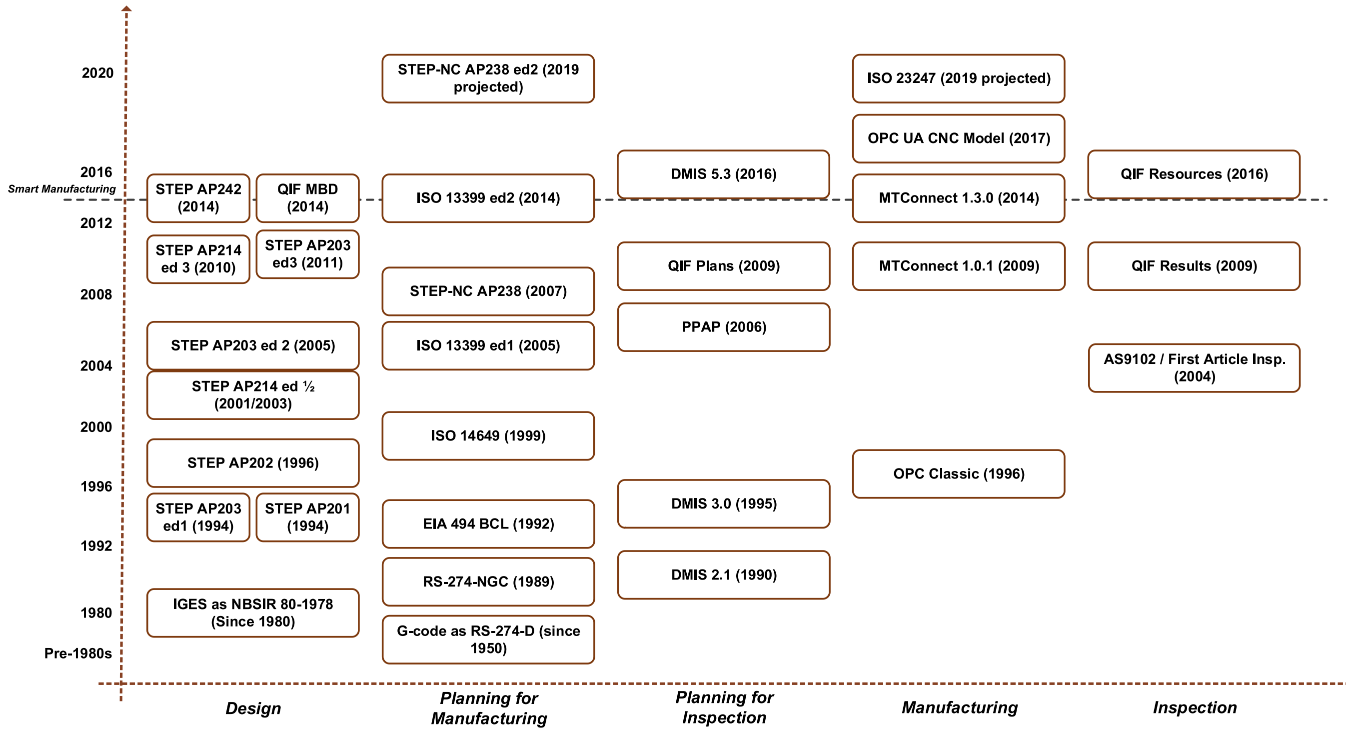

Fig.5. Timeline-based depiction of standards for Digital Twin in the manufacturing domain (Enriched from [26]).

4.1.1. Information models for product Digital Twin

The most predominant standards for developing product Digital Twin are ISO 10303 [27] and ISO 14649 [28] standards. ISO 10303 [27], known as STEP, provides a neutral data structure for exchanging product data between CAD systems. Its latest development of AP242 [29] for 'Managed Model Based 3D Engineering' by merging AP203 and AP204, with a focus on the representation of 3D model data, geometric tolerance and PMI (Product Manufacturing Information), provides a sound technological base for global design and manufacturing collaboration. Geometric tolerance and PMI information can now be read by machines directly from product design files in STEP AP242 model without the need of interpreting 3D drawings. This change closes the communication gaps between various stages of the product lifecycle, resulting in autonomous process planning, manufacturing, inspection, and so forth.

ISO 14649 [28] and ISO 10303-238 [30] (also known as STEP-NC) are proposed to replace the RS274D (ISO 6983) M and G code via a modern associative language that directly connects the CAD design data used to determine the machining requirements for operation with the downstream fabrication processes. STEP-NC allows manufacturing organizations to share machining information between machines seamlessly via the exchange of semantic-enriched 'what-to-do' information. It relies on intelligent machine tools to interpret 'how-to-do' instructions adaptive to the local machining conditions. The shift of interpreting local machining instructions into the machine controller level maximizes the interoperability between distributed machine tools.

4.1.2. Information models for production Digital Twin

ISO 13399 [31] is an international standard by ISO for the computer-interpretable representation and exchange of industrial product data about cutting tools and tool holders. It provides a neutral mechanism capable of describing product data regarding cutting tools. This information model has been used for CAD/CAM/CNC integration, tool management, product data management and manufacturing resource planning. Similarly, ISO 14649-201 [32] defines a model for specifying machine tool data required for cutting processes.

Targeting at describing machine tools, MTConnect standard offers a semantic vocabulary for manufacturing equipment to provide structured, contextualized data with no proprietary format [33]. It is developed to translate manufacturing data into a common, internet-based language interpretable by software applications. MTConnect defines a hierarchical information model for machine tools. The information model represents the logical structure of a machine tool, including the components, the available data and the relationships between them.

OPC Unified Architecture (OPC UA) [34] is another open standard that specifies information exchange for industrial communication on devices within machines, between machines and from machines to systems. A widely-recognized OPC-UA information model is MTConnect-OPC-UA companion specification, aiming at improving the interoperability between these two standards. MTConnect-OPC UA companion specification ensures interoperability and consistency between MTConnect specifications and the OPC UA specifications, as well as the manufacturing technology equipment, devices, software, or other products that implement those standards.

It is common that the information model from a single standard cannot meet the application requirements because of the breadth of the potential application of Digital Twin. Past studies suggest a systematic information model development process to ensure maximum standard conformance and usability [35]. MTConnect and OPC-UA community also recommend a bottom-up approach to expanding existing information models to suit new application needs, especially when now IT disruptions outpace the manufacturing standard development.

4.2. Industrial communication – twinning tools

A communication network is another critical factor for enabling the establishment of Digital Twins. State synchronization between a Digital Twin and its counterpart in the physical space relies on bi-directional and real-time data communication. State changes to a physical object are detected by sensors and transmitted to its Digital Twin in the cyberspace. In this regard, industrial communication protocols can help collect data from physical devices.

Table 1 presents a list of industrial communication protocols used for industrial process monitoring and control. These protocols are

Table 1
Popular industrial communication protocols mapped to the OSI model ([36–44]).

Protocol	Physical	Data link	Network	Transport	Session	Presentation	Application	Data Rate	No. of Devices
ControlNet [36]	RG-6 coaxial cables, 5Mbps	ControlNet CTDMA	ControlNet, 99 nodes	ControlNet	CIP protocol family			<5Mbps	99
DeviceNet [37]	CANbus with twisted pair cables, 1Mbps	CAN bus CSMA/NBA	DeviceNet, 64 nodes	DeviceNet	CIP protocol family			<0.5Mbps	64
Modbus-RTU or ASCII [38]	Serial cable, ex: RS-232, RS-485	Modbus	Modbus Map, 247 nodes	Modbus			Modbus client or server + interface	19.2kbps (default)	<247
PROFIBUS [39]	RS-485 cables, fiber optic cable or MBP	PROFIBUS Fieldbus data link	32 nodes, 126 with fiber optic cable	Not used	Not used	Not used	PROFIBUS DP	<12Mbps	<126
PROFINET [40]	Ethernet 10/100/1000 Mbps	Ethernet CSMA/CD	IP	TCP/UDP	Not used	Not used	PROFINET	<1000Mbps	>1000
Modbus-TCP/IP [41]	Ethernet 10/100/1000 Mbps	EtherNet	IP, 254 nodes/module	TCP port 502	Modbus TCP		Modbus client or server + interface	<1000Mbps	>1000
EtherNet /IP [42]	Ethernet 10/100/1000 Mbps	Ethernet CSMA/CD	IP	TCP/UDP	CIP protocol family			<1000Mbps	>1000
EtherCAT [42]	Ethernet 10/100/1000 Mbps	EtherNet w/EtherCAT slave&controller chip	IP with timing layer, up to 65535 nodes	TCP/UDP	EtherCAT			<1000Mbps	>1000
HART (Wired) [43]	Simultaneous hybrid analog & digital signaling, 4-20mA copper wiring	Mechanical/electrical connection transmits raw bitstream		Auto segmented transfer of large data sets, reliable stream transport, negotiated segment sizes	Not used	Not used	Command oriented, predefined data types and application procedures	1.2kbps	62
HART (Wireless) [44]	2.4GHz wireless, IEEE802.15.4 based radios, 10dbm transmission power	Secure and reliable, time synched TDMA/CSMA, frequency agile with ARQ	Power-optimized, redundant path, self-healing wireless mesh network		Not used	Not used		<250kbps	<30000

mapped to the ISO Open Systems Interconnection (OSI) model but very often modified (or simplified) to satisfy the real-time and reliability requirements of industrial processes. Existing industrial systems are typically implemented with heterogeneous networks. These industrial networks can be classified into three different categories. The first category consists of the earliest development of industrial networks, or the so-called Fieldbus, which represents the common legacy networks in existing industrial automation systems. The second category is the next generation of industrial networks, which are typically Ethernet-based protocols but with modifications to satisfy the real-time and reliability requirements. The third category is the recent development following the trend of the Internet of Things that typically makes use of wireless network technologies.

4.2.1. Fieldbus networks

In the late 1970s to late 1980s, several dedicated industrial networks (or Fieldbus), such as PROFIBUS [39] and Modbus [38], were developed to support the machine to machine communications and the remote terminal control of programmable logic controllers, for process and peripheral control/automation. As shown in Table 1, many Fieldbus protocols were designed to operate on different physical media and have widely incompatible communication stacks across different layers of the OSI model. This has thus lead to closed-loop silos which prevents data exchange and communication between standards. The current trend is moving towards adopting Ethernet-based standard, such as Modbus/TCP [41], in order to facilitate inter-communication at a higher level (e.g., the Internet or the enterprise control system).

Table 1 also provides a high-level comparison between different types of industrial networks in terms of their communication data rate and the number of supported devices on a single network. While the performance varies significantly among the three categories, it should be noted that the data rate and the number of supported devices in a specific network are heavily influenced by the selected physical medium, operation mode (and hence communication overhead), network topology, and the length of the physical medium (e.g., cable length). While Fieldbus networks seem to offer a slower data rate and fewer devices, their key advantage is usually the deterministic communication time for safety-critical operations.

4.2.2. Ethernet-based industrial networks

An increasing number of manufacturers are using Industrial Ethernet-based solutions to connect systems. This is driven by the need of high-performance integration between factory installations and the Industrial Internet of Things [45]. The advantages of Industrial Ethernet over traditional Fieldbus systems are its homogenous network infrastructure, ease of integration with the Internet, greater bandwidth to transmit safety-critical data, and the ability to communicate over longer distances. Even with the adoption of a common Ethernet standard, devices that support different Industrial Ethernet standards are not compatible or interoperable with each other because of the unique protocol stacks in different Industrial Ethernet standards. The future Ethernet IEEE 802.1 TSN (Time Sensitive Networks) standard could eventually make time-critical and deterministic network communication via standard Ethernet components possible, thus facilitating wider adoption and better interoperability.

4.2.3. Industrial wireless networks

One of the key driving features in Digital Twin and throughout the automation and manufacturing industries is the need for data/information exchange. This is evident from the early development of the Fieldbus systems. Since 2000, the concept of IoT and Wireless Sensor Networks (WSN) are also impacting the industrial network field. Most of modern approaches are adopting existing standards such as IEEE 802.11 [46] (e.g., WiFi-based), IEEE802.15.1 (e.g., Bluetooth-based), and IEEE 802.15.4 [47] (e.g., Zigbee-based). While wireless networks have the intrinsic benefit of ease of installation due to no wiring and low cost, existing approaches are still limited due to the lack of reliability and potentially long latency for safety-critical and real-time data.

4.3. Big data processing

The data gathered from various sources to construct a Digital Twin will be Big Data [48], if not now. Efficient processing of Big Data gathered from the physical space is the third pillar of developing a Digital Twin.

Data processing methods that use statistical analysis and prediction models while ignoring noise and conflicts between single data records do not apply to Digital Twin development by default. The following unique features need to be considered for Big Data analysis solutions targeting Digital Twin industrial applications.

- **Hidden Meaning** – Feature extraction in industrial Big Data analysis needs to analyze the meaning of a feature and the relations between features in the real world, in addition to statistical analysis of feature relations.
- **Timeliness** – Industrial data analysis requires low-latency data processing to enable time-sensitive applications, such as cloud-based industrial control [49].
- **High Quality** – Data quality is sometimes more important than its volume. Industrial Big Data applications need high-quality data that covers the full spectrum of the system/process to be analyzed. Noise and data conflicts can directly break data analysis and result in unusable results.

Therefore, there exists a demand for a low-latency data processing system that can integrate domain knowledge verification for data processing. To this end, we propose the following general data processing framework for constructing Digital Twins as shown in Fig. 6.

4.3.1. Data acquisition and cleansing

Real-world data collection comes with noise and missing data. It is essential to clean low-quality raw data into ordered, meaningful and simplified forms.

A missing value is a datum that has not been stored or gathered due to a faulty sampling process, cost restrictions or limitations in the acquisition process. Inappropriate handling of the missing values will easily lead to poor knowledge extraction and wrong conclusions [19]. One option is to discard the instances that may contain a missing value. However, this approach is rarely beneficial, as eliminating instances may produce a bias in the data processing process, and a Digital Twin can miss some critical snapshots. Another method is to use a statistical method to 'guess' an approximate value to fill the missing values. This method can be a good choice if integrated with domain knowledge reasoning. There are physical models behind activities occurring in the manufacturing environment. The domain knowledge can be used as the base rules for making a reasonable prediction of the missing value.

Conflicting or redundant data records can introduce bias in the data

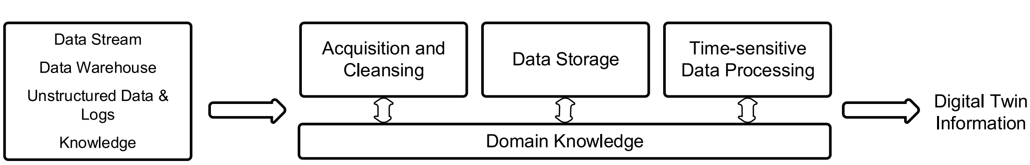

Fig. 6. Data processing for industrial big data.

Table 2
Representative data storage options.

Type	Database	Description	Application	Example
Non-relational database	Key-value database	A data model that pairs a unique key and its associated value in storing data elements	Used for storing clickstream data and log files, such as CPS log files	Aerospike, DynamoDB, Redis, Riak
	Document database	Stores data in document-like structures that encode information in formats such as JSON	Content management and monitoring web and mobile applications	Couchbase Server, CouchDB, MarkLogic, MongoDB
	Graph Database	Emphasizes connections between data elements, storing related 'nodes' in graphs to accelerate querying	Recommendation engines and knowledge base	AllegroGraph, IBM, Neo4j
	Column stores	Stores data across labels that can have a huge number of columns	Internet search and other large-scale Web applications	Accumulo, Cassandra, HBase, Hybertable, SimpleDB
Relational database	SQL database	Stores information in structured tables with rows and columns	Complicated query, database transactions, and data analysis	MySQL, PostgreSQL, Microsoft SQL Server

analysis results. Two main approaches can be used to solve the problem. The first one is to correct the noise by using data polishing [50], primarily when the data affects the annotation of a physical-related status. The second method is to use noise filters [51], which identifies and removes the noisy instances in the data while maintaining the representation of the physical state of the object to be modeled. Both methods require extensive use of domain knowledge to drive the polishing and filtering decisions to ensure corrective actions can be taken so that the nature of the data set is not changed.

4.3.2. Data storage

There is a multitude amount of data storage options tailored to different kinds of data formats and application requirements, which are classified as relational databases and non-relational databases (as shown in Table 2). Relational databases are good choices for applications that involve the management of complex database transactions and heavy data analysis, because of referential integrity.

Non-relational databases are geared towards managing large sets of varied and frequently updated data, often in distributed systems. They avoid the rigid schemas associated with relational databases. The architectures vary and are separated into four primary classifications, each of which is suitable for different application scenarios as listed in Table 2.

In the context of smart manufacturing, key-value databases can be used for storing software log files from connected CPSs. Similarly, documents can be stored in document databases to ensure high flexibility and durability. Engineering knowledge can reside in graph databases to accelerate querying and reasoning. Column stores allow for fast querying and processing and it is heavily used for big-data analysis where speed is critical. In practice, these databases will need to complement each other to ensure low latency.

4.3.3. Time-sensitive data processing

Digital Twin applications, such as real-time monitoring, prediction, and control impose a stringent latency requirement for the data processing architecture [52]. A 'designed for latency' data processing architecture becomes a critical criterion.

Parallel computing technologies can ensure low-latency data processing. The essence of data parallelism paradigm is to divide a computational task into a cluster of similar sub-tasks that can be processed independently and whose results are combined afterwards, upon completion. MapReduce is one such technology that has been widely used. Recognizing its limitation for stream analytics [53], some competitors emerged as an alternative, capable of performing stream analysis. Apache Spark is a large-scale data processing engine for both batch and stream processing. Apache Flink later emerged as a better option because of its built-in streaming processing, instead of using micro batching to handle stream processing. Apache Storm is an open-source distributed real-time processing platform. Besides, some other streaming engines can be used where appropriate, such as Kafka Streams and Google Dataflow.

Though the above technologies provide the foundation for Big Data processing, high-performance processing of time-series data is the key to the successful implementation of a Digital Twin. This is due to two reasons: (1) data gathered from the physical world are mostly discrete time data, and (2) there is timeliness requirement for a Digital Twin, regardless of the latency requirement between a Digital Twin and its physical counterpart. The effective handling of time-series data to construct a Digital Twin can ensure a required latency between a Digital Twin and its physical counterpart.

5. Application scenarios

Although Digital Twin is a relatively new concept, some practical applications of Digital Twin have already been developed and reported in the literature. This section briefs the current status of Digital Twin

Table 3
Overview of existing Digital Twin applications.

Source	Digital Twin type	Physical object	Information model	Data communication standard	Benefit(s)/Purpose(s)
[54]	Manufacturing asset	Grinding wheel	Numerical models	Universal Asynchronous Receiver Transmitter (UART)	Improve energy and resource efficiency of grinding process
[55]		Satellite assembly system	CAD model + Behavior model + Rule model	–	Smart production management and control
[56]		Manufacturing cell	–	–	Comprehensive simulation-based system engineering
[57]		3D printer	MTConnect	MTConnect	Digital Twin-enabled cyber-physical cloud manufacturing
[58]		3D printer	Proprietary ontology	HTTP	Cloud-based bidirectional communication between machine and Digital Twin
[59]		Welding production line	CAD model + OPC-UA	OPC-UA	Digital Twin for product life cycle management
[60]		Engine parts	–	–	Digital Twin-based smart process planning
[61]		Core making machine	CAD model + Kinematic model	OPC-UA	Digital Twin for machine reconditioning (significant reduction of the commissioning time)
[62]		Hot rolling production line	–	–	Optimization of hot rolling production line scheduling
[63]		Drilling system and crane	–	–	Monitor machine conditions and operator performance at a low cost
[64]		Production system	–	–	Tutoring service, augmented assistance, in-line diagnostics, and condition monitoring service
[65]		Factory	–	–	Digital Twin to improve factory design
[66]		Rotating machinery	Finite element model	–	Digital Twin for rotating machinery fault diagnosis
[67]		Waste electrical and electronic equipment	Extended ISO 10303 standard	–	Digital Twin-based system for the WEEE recovery to support the manufacturing/ remanufacturing operations throughout the product's life cycle
[68]		Machine tool	MTConnect	MTConnect	Comprehensive machine tool and machining process monitoring, decision-making support for humans
[69]		Machine tool	–	–	Machine tool operation monitoring, surface roughness prediction
[70]		Automotive production cell	–	–	Digital Twin for monitoring energy consumption
[71]		Multi-robot systems	–	–	Digital Twin for just-in-time planning of intelligent multi-robot systems with improved execution time
[72]		Machine tool	FDI (factory design and improvement) model	–	Machine tool status monitoring
[24]		3D printer	–	–	Digital Twin of 3D printers for rebuilding digital part and data visualization
[73]		Industrial valve	–	PLCopen	Exchange data between Digital Twin and other systems
[74]		Robots	Multibody dynamics model	–	Digital Twin enabled VR testbed, robot control, and manual guidance
[75]		Part	STEP/ G code	MTConnect	Linking as-planned to as-fabricated product data
[76]	Factory	Production line	Proprietary 3D model	Ethernet + OPC	Digital Twin to support decision-making over the system design and solution evaluation
[77]		Warehouse	Proprietary 3D model	–	Digital Twin enabled VR testing environment
[8]		Shop floor	–	–	Digital Twin of shop floor to support smart operations in the manufacturing process
[78]		Industrial work cell	Unified Robot Description Format(URDF) + Simulation Description File (SDF)	Modbus TCP/IP + Ethernet IP	A simulator based on Digital Twin for a flexible framework of work cell
[79]	People	Employee	–	–	Digital Twin of employees to support Intelligent control of an assembly station

applications. First, an overview of existing Digital Twin applications is provided, and the current status of Digital Twin applications is discussed. Second, three representative Digital Twin applications are introduced to demonstrate the advantages and potential of Digital Twin.

5.1. Overview of existing digital twin applications

Existing Digital Twin applications reported in the literature have been reviewed and summarized in Table 3. The details of each Digital Twin application are also briefly mentioned, including (1) the type of the Digital Twin, i.e., manufacturing asset, human, factory or production network), (2) the physical object of the Digital Twin, (3) the information model of the Digital Twin, (4) data communication standard used in the application, and (5) the benefit(s) or purpose(s) of the Digital Twin application.

It can be seen that compared to the total number of publications on Digital Twin, most of the existing research on Digital Twin is conceptual work, development of practical Digital Twin applications is still at an early stage. Key findings are as follows:

- **Digital Twin type**: 85% of Digital Twin applications are developed for manufacturing assets; 11% are developed for factories; only one Digital Twin application for people has been identified, and there is no Digital Twin application for production networks. This shows that prior Digital Twin research mainly focused on manufacturing devices; the importance of the involvement of human in the Digital Twin environment has been overlooked. Besides, the lack of applications for production networks indicates that research on communication/interactions between Digital Twins has not attracted much attention.
- **Information model**: For the Digital Twin for manufacturing assets, information models that describe the data structure and semantics are mostly used, including different types of data models (MTConnect, OPC-UA, AutomationML and so forth) and databases. However, the information model for a factory Digital Twin has not been explored to depth. Whether this should be an integration of existing information models for manufacturing assets or should be a standard that governs all still needs to be addressed.
- **Data communication standard**: Only a few applications have used unified data communication standards for modeling a Digital Twin. This issue can severely limit the interoperability and accessibility of a Digital Twin. It may also be the main reason why no Digital Twin application for production networks has been developed so far.
- **Purpose/benefit**: Most applications are developed to provide monitoring functions (status monitoring, process visualization, fault diagnosis, and so forth) and prediction functions (fault prognosis, product lifecycle management, process optimization, and so forth). Most applications can be seen as decision-making support applications for humans; while very few of them have included direct/autonomous feedback control from Digital Twin to a physical object.

5.2. Representative applications

Though the development of Digital Twin applications is still at a very early stage, several full-fledged Digital Twin applications have emerged. Here, we discuss some of the important application scenarios.

5.2.1. Digital Twin machining

STEP Tools Inc. developed a Digital Twin Machining application [80] that enables real-time quality inspection of machining results. Fig. 7 shows the system framework of Digital Twin Machining. The Digital Twin is enabled by the utilization of four standards: 1) STEP [27], 2) STEP-NC [28], 3) MTConnect [33], and 4) Quality Information Framework (QIF) [81].

STEP AP242 [29] is used to describe the design information of a workpiece. The manufacturing solutions, including all the operations, setups, tool paths, tool requirements, and in-process tolerances, are communicated via STEP-NC AP238 protocol [30]. MTConnect is used to monitor the machining results. It allows the machine tool status and coordinates to be streamed to the Digital Twin in real time (100 Hz). The MTConnect data stream also includes measurement results as reported by touch probes to enable tolerance evaluation. QIF is used to report the results of the quality evaluations. The utilization of these standards provides the Digital Twin Machining solution with great interoperability.

The Digital Twin functions as a server that allows Web-based applications to access all the data in the Digital Twin. In the Digital Twin Machining application developed by STEP Tools Inc., the models of workpieces, cutters, fixtures, as well as operations and tool paths are fully assembled to perform real-time machining simulation. During real machining processes, the assembled model is updated in real time to show the machining results on the Digital Twin. Operators can remotely monitor the machining processes using mobile devices that support standard Web browsers. Measurements can be made on the Digital twin and alerts can be sent if tolerances are not being met. Thus, the Digital Twin Machining enables “build it here, build it now and build it right,” as claimed by STEP Tools Inc.

5.2.2. Digital Twin for a rotor system

Wang et al. [66] developed a Digital Twin application for rotating machinery fault diagnosis that can identify the fault parameters of a rotor system and perform quantitative diagnosis of the rotor system. The overall system architecture of the developed application is shown in Fig. 8.

Since the main purpose of this application is the fault diagnosis for rotating machinery, modeling of the Digital Twin mainly considers the dynamic behavior of the rotor system. Hence, the Digital Twin of the rotor is constructed using a finite element model that includes the geometry, dynamics and material properties of the rotor. The critical speed and unbalance response of the rotor under different conditions are obtained by finite element analysis. Four displacement sensors and a data acquisition system were implemented to collect the vibration signals from the rotor system.

The rotor unbalance fault quantification and localization were performed to realize the fault diagnosis. Compared with traditional fault diagnosis methods, the developed Digital Twin application enables unbalance quantification and localization for fault diagnosis, which further enables accurate diagnosis and adaptive degradation analysis of rotating machinery.

5.2.3. Digital Twin enabled Cyber-Physical Machine tool

Aiming at advancing legacy machine tools to Cyber-Physical Machine Tools (CPMT) [83], Liu et al. [68] developed an MTConnect-based CPMT where the Digital Twin of the machine tool is a core component. Fig. 9 shows the system architecture of the developed MTConnect-based CPMT. Real-time machining data were collected from the CNC controller and embedded sensors and communicated through to the Digital Twin via MTConnect standard.

The implementation of MTConnect standard significantly improved the interoperability of the machining data and hence the accessibility of the Digital Twin. A prototype of a machine tool monitoring system was developed to enable near real-time remote machine monitoring.

6. Research issues

Based on the discussions in the above sections, we summarize the following key research issues for advancing the research of Digital Twin-driven smart manufacturing.

<u>Research issue 1: architecture pattern for a Digital Twin</u>

There exist two system architecture patterns, namely server-based and edge-based. In server-based architecture, the data acquired from a physical device is routed back to a centralized server that performs the

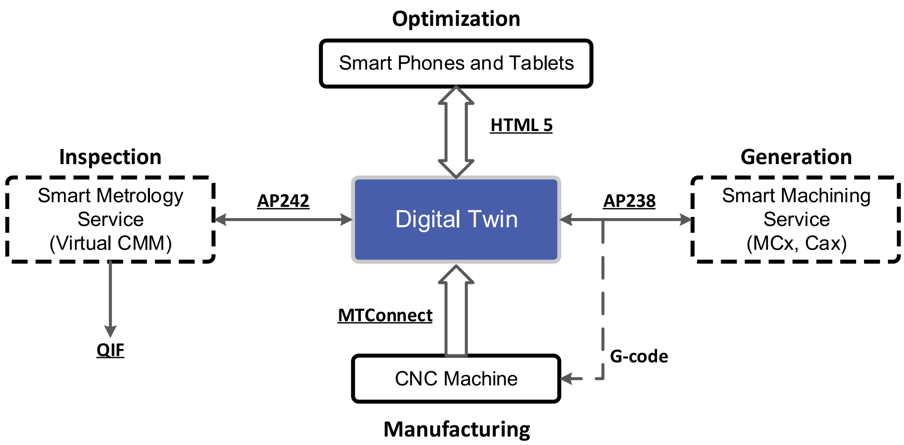

Fig. 7. System framework of the Digital Twin Machining [82].

data analysis and Digital Twin construction. This pattern provides economies of scale and facilitates easy maintenance. In edge-based architecture, some data analysis is applied at the 'edge' of the system. That is, data pre-processing is performed locally and on the raw data captured from a physical device. As a result, edge-based architecture should be more effective on low-latency data processing if designed well. However, this pattern is more complicated to maintain.

Research issue 2: communication latency requirement for a Digital Twin

Latency requirement is application-driven. The application scenario determines the required communication latency between a physical device and its Digital Twin. This is because the system development costs and difficulties increase significantly as the communication latency requirement becomes stringent. In practice, Digital Twin-based shop floor monitoring can accept higher latency than cloud-based industrial control. BMWi, Germany [85] specifies the nominal communication latency for various manufacturing applications, which can be used as a guideline for designing the system architecture of a Digital Twin application.

Research issue 3: data capture mechanism

Two common methods can be used to gather data from physical devices, i.e., capturing changes and taking snapshots. There is extensive use in large scale computer systems for both methods, and sometimes a system uses a mix of them. Both methods need to be validated for specific application cases.

Research issue 4: standards for Digital Twin

Though anyone can develop a Digital Twin solution using common technologies, standards will facilitate the longevity of a Digital Twin solution. Standard-compatible Digital Twin solutions can inherit the flexibility, interoperability and scalability of existing and new standards for information model and communication protocols. This is especially important when a Digital Twin will be deployed in an open network of Digital Twins. Recognizing the need for standardization, ISO is actively developing a dedicated standard for Digital Twin manufacturing [9].

Research issue 5: functionalities of a Digital Twin

Existing Digital Twin applications are mainly developed for monitoring and prediction purposes and used as decision-making support applications for humans. Though human involvement in the smart manufacturing environment is essential, direct/autonomous feedback control from the Digital Twin to the physical world should be

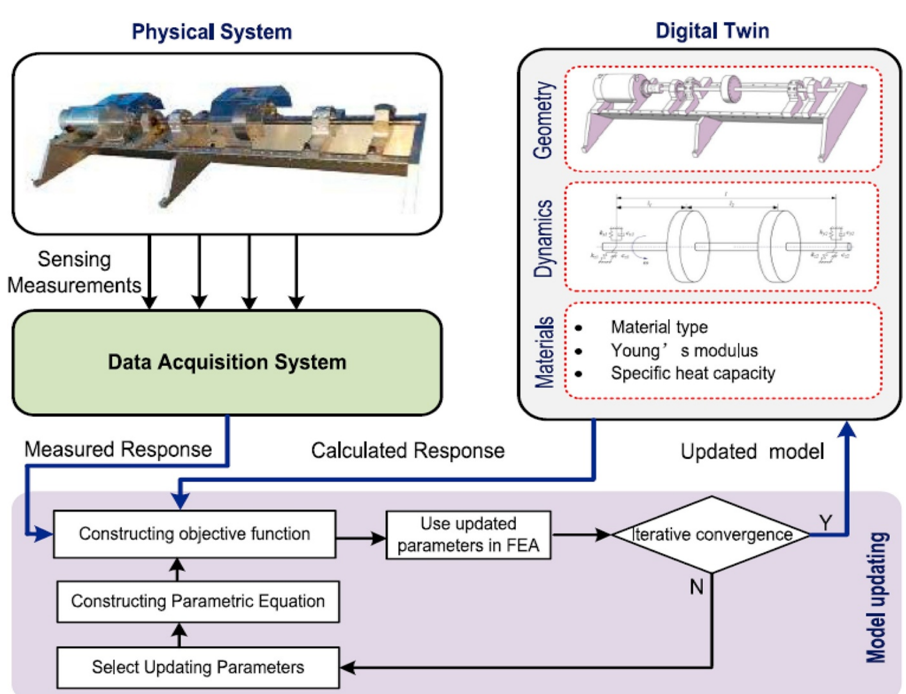

Fig. 8. Digital Twin for rotating machinery fault diagnosis [66].

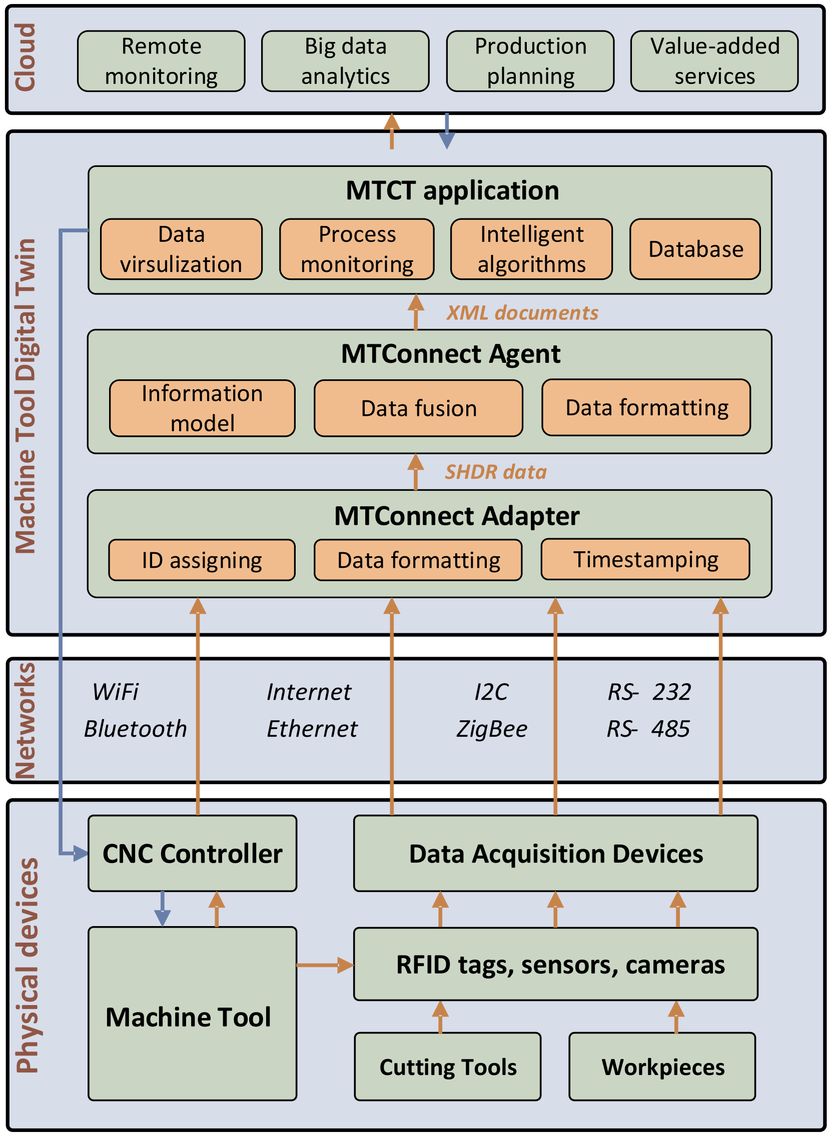

Fig. 9. MTConnect-based Cyber-Physical Machine Tool [84].

developed. Hence, the Digital Twin application can endow the physical objects with a certain degree of autonomy.

Research issue 6: Digital Twin model version management

A Digital Twin model can evolve over time as a result of engineering changes to its physical counterpart, changes to the modelling interests throughout the lifecycle of the physical counterpart, or other cases. In these cases, the different versions of a Digital Twin models over time should be captured, stored and integrated. Snapshot-based and change-based version management principles can be applied for the effective management different versions of a Digital Twin model.

Research issue 7: humans in Digital Twin applications

Humans play an important role in the Digital Twin-driven smart manufacturing environment. While some low-level operations can be autonomously achieved without human intervention, many decision-making activities have to be performed by humans. Though some new interaction technologies such as AR have been studied and implemented in a manufacturing environment to improve human-machine interactions, humans are still not considered as an integral part of the smart manufacturing system. Significant research effort needs to be made on the topic of Digital Twin for people in the smart manufacturing environment in the future.

7. Conclusions

This paper presents the current status and advancement of Digital Twin-driven smart manufacturing. The core concept, reference model, enabling technologies, application scenarios, and research issues of Digital Twin-driven smart manufacturing are discussed in detail.

With the rapid growth of integrating information technologies and operation technologies in the industry, significant efforts have been made to make manufacturing smart. As a core element of future manufacturing, Digital Twin-driven applications are going to challenge and change the fundamentals of manufacturing systems and operations. The convergence of the digital world and physical world enables smart decisions to be made at every single point of manufacturing operations, thus can foster a data-driven smart manufacturing environment.

As can be seen from the literature, nearly 500 articles related to Digital Twin in the engineering domain have been published since 2016, and the number is proliferating, together with huge interest from the industry. R&D in this area needs to follow a common reference model. The authors believe that constructing a Digital Twin needs a standardized information model, high-performance data processing, and industrial communications to work together. Existing standards in the manufacturing and industrial control domain need to be used where appropriate. The dedicated standard for Digital Twin smart manufacturing being developed by ISO can be the starting point for consolidating research efforts in this space.

The research activities are going to stay active due to the challenging issues of constructing a reliable Digital Twin in practice. This is especially true for manufacturing applications, which pose stringent requirements on timeliness, accuracy, and reliability. The authors believe researches on standards, communication protocols, time-sensitive data processing, and reliability need to be the priorities for the next stage of the research while focusing on application scenarios of Digital Twin.

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