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Digital Twins and Cyber–Physical Systems toward Smart Manufacturing and Industry 4.0: Correlation and Comparison

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ABSTRACT

State-of-the-art technologies such as the Internet of Things (IoT), cloud computing (CC), big data analytics (BDA), and artificial intelligence (AI) have greatly stimulated the development of smart manufacturing. An important prerequisite for smart manufacturing is cyber–physical integration, which is increasingly being embraced by manufacturers. As the preferred means of such integration, cyber–physical systems (CPS) and digital twins (DTs) have gained extensive attention from researchers and practitioners in industry. With feedback loops in which physical processes affect cyber parts and vice versa, CPS and DTs can endow manufacturing systems with greater efficiency, resilience, and intelligence. CPS and DTs share the same essential concepts of an intensive cyber–physical connection, real-time interaction, organization integration, and in-depth collaboration. However, CPS and DTs are not identical from many perspectives, including their origin, development, engineering practices, cyber–physical mapping, and core elements. In order to highlight the differences and correlation between them, this paper reviews and analyzes CPS and DTs from multiple perspectives.

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1. Introduction

With the advancement of data-acquisition systems, information technology (IT), and network technologies, manufacturing has entered the digital age. Against a background of digitalization, the manufacturing industry is facing global challenges with rapid advancements in digital technologies [1]. In this context, advanced manufacturing strategies have been initiated, such as the Industrial Internet, Industry 4.0, and the corresponding initiative in China. The common aim of these strategies is to achieve smart manufacturing [2], which is also commonly known as intelligent manufacturing. However, a detailed comparison reveals a difference between the concepts of intelligent manufacturing and smart manufacturing. Intelligent manufacturing has been in use since the 1980s, as the intersection of artificial intelligence (AI) and manufacturing [3,4]. As AI evolves into AI 2.0, however, smart technologies such as the Internet of Things (IoT), cloud computing (CC), big data analytics (BDA), cyber–physical systems (CPS), and digital twins (DTs) are taking a central position in new-generation intelligent manufacturing—that is, smart manufacturing [4,5]. Manufacturing is shifting from knowledge-based intelligent manufacturing to data-driven and knowledge-enabled smart manufacturing, in which the term "smart" refers to the creation and use of data [4]. Therefore, smart manufacturing can be considered to be a new version of intelligent manufacturing that highlights the use of advanced information and communication technology and advanced data analytics [6]. The term smart manufacturing refers to a future state of manufacturing, in which real-time transmission and analysis of data from across the product life-cycle, along with model-based simulation and optimization, create intelligence to yield positive impacts on all aspects of manufacturing [7,8]. Cyber–physical integration is an important prerequisite for smart manufacturing, as well as being its core. As the preferred means of such integration, CPS and DTs have gained close attention from academia, industry, and government. Smart manufacturing can be considered a specialization of the prominent technologies of CPS and DT.

CPS are multidimensional and complex systems that integrate the cyber world and the dynamic physical world. Through the integration and collaboration of computing, communication, and control, known as the "3C," CPS provide real-time sensing, information feedback, dynamic control, and other services [9,10].

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With intensive connection and feedback loops, physical and computing processes are highly interdependent [11]. In this way, cyber–physical integration and real-time interaction are achieved in order to monitor and control physical entities in a reliable, safe, collaborative, robust, and efficient way [10].

The DT is another concept associated with cyber–physical integration. A DT creates high-fidelity virtual models of physical objects in virtual space in order to simulate their behaviors in the real world and provide feedback [12]. A DT reflects a bi-directional dynamic mapping process; it breaks the barriers in the product life-cycle and provides a complete digital footprint of products [13]. As a result, DTs enable companies to predict and detect physical issues sooner and more accurately, optimize manufacturing processes, and produce better products [14].

By definition, both CPS and DTs are used to describe cyber–physical integration. However, why do these two concepts exist in parallel, and why are they used in different fields? What are the differences and correlation between them? What are their respective core elements? And which is more suitable in practice? In order to highlight the differences and correlations between CPS and DTs, this paper reviews and analyzes them from multiple perspectives, including their origin, cyber–physical mapping, hierarchical modeling, and core elements.

The rest of this paper is organized as follows: Section 2 reviews the origin and development of CPS and DTs and Section 3 analyzes the cyber–physical mapping relationship. A hierarchical model of CPS and DTs in manufacturing is presented in Section 4. In Section 5, their core elements are discussed, followed by a comparison of CPS and DTs in Section 6. Finally, conclusions are drawn in Section 7.

2. Origin and development of CPS and DTs

As shown in Fig. 1, with the evolution from traditional IT to new IT, the low cost and improved power of new IT contributed significantly to the emergence and use of CPS and DTs. As the preferred means of cyber–physical integration, CPS and DTs pave the way for smart manufacturing, which will fundamentally transform existing manufacturing systems and business models.

2.1. Origin and development of CPS

CPS were derived from the extensive application of embedded systems; their origin can be traced back to 2006. The phrase "cyber–physical system" was coined by Helen Gill at the National Science Foundation (NSF) to describe increasingly complex systems that could not be effectively illustrated using traditional IT terminology [15]. CPS were subsequently listed as a top priority issue for research investment in the United States [14]. In Germany, CPS are considered to be the core and foundation of Industry 4.0 [16]. There is no doubt that CPS can bring huge economic benefits and will fundamentally change existing industrial operations [10]. However, current research on CPS mainly focuses on discussions of the concept, architecture, technologies, and challenges [17], while cases of CPS in engineering practice are in their relative infancy. In comparison with embedded systems, the IoT, sensors, and other technologies, CPS are more foundational, as they do not directly reference implementation approaches or particular applications [11]. Thus, CPS are more akin to a scientific category than an engineering category, as was implied by the NSF announcement that the research initiative on CPS is to seek out new scientific foundations and technologies [18].

2.2. Origin and development of DTs

The term "DT" was first presented by Michael Grieves in a 2003 presentation on product lifecycle management (PLM) at the University of Michigan [12]. At that time, almost no relevant studies or applications were available, due to the limitations and immaturity of the technology [12]. In order to solve increasingly complex engineering system problems, National Aeronautics and Space Administration (NASA) and the US Air Force applied DTs in their health maintenance and for the remaining useful life prediction of aerospace vehicles [1,19]. At present, advances in new IT are enabling the growth of DTs. Since DTs open up a new way to synchronize physical activities with the virtual world, they have become a popular research topic. Recently, DTs have also been adopted in various industries for purposes including product design [20], production line design [21], DT shop floors [22], production process optimization [23], and prognosis and health management [24]. DT industrial practices can also be observed in several large enterprises, such as General Electric, Siemens, PTC, Dassault Systems, and Tesla [25], which use DTs to increase their product performance, manufacturing flexibility, and competitiveness [25]. When looked at from this perspective, the engineering applications of DT are pervasive. Therefore, compared with CPS, DT is akin to an engineering category.

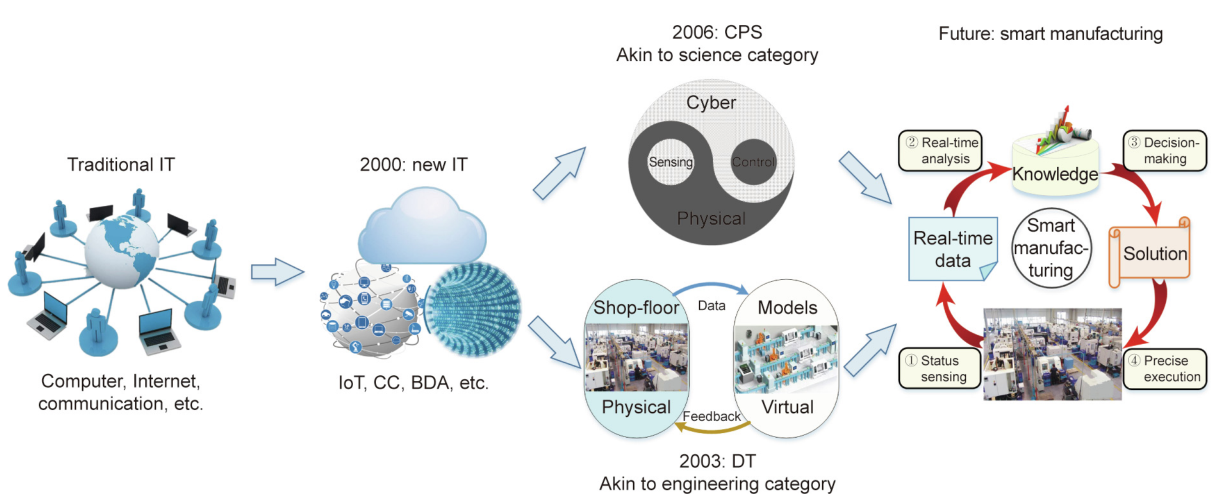

Fig. 1. Origin of CPS and DTs toward smart manufacturing.

2.3. Recapitulation

From the perspective of their origin and development, both CPS and the DT benefited from the advances in new IT, causing them to emerge almost simultaneously. As effective means of achieving cyber–physical integration, both have drawn considerable attention from researchers in related fields and from practitioners in industry. However, in comparison with each other, CPS are akin to a scientific category, while DTs are akin to an engineering category. In industrial practices, engineering systems can achieve higher precision and better management by means of DT technology.

3. Mapping between physical and cyber/digital worlds in CPS and DTs

CPS are defined as the integration of computational and physical processes [26], whereas the concept of using a digital copy of a physical system to perform real-time optimization is referred to as a "DT" [27]. In manufacturing, both CPS and DTs include two parts: the physical part and the cyber/digital part. As shown in Fig. 2, the physical part consists of various manufacturing resources, which can be summarized as "human/machine/material/environment" [4]. The manufacturing activities are executed by these physical resources. The cyber/digital part, which has various ubiquitous apps and services, incorporates smart data management, analytics, and computing capabilities [18]. Services and apps offer rich functions that allow the participators in manufacturing to improve productivity. The physical part senses and collects data, and executes decisions from the cyber/digital part, while the cyber/digital part analyzes and processes data, and then makes decisions [9]. Through this intensive connection, the cyber/digital part can affect physical processes and the physical part can affect cyber/digital processes [28]. For example, in the Wise-ShopFloor designed by Wang et al. [29–31], the cyber–physical interaction provides users with an intuitive shop-floor environment in which real-time monitoring and remote control are undertaken. The Java 3D model, which provides users with visualization from various perspectives, is driven by real-time sensor signals [31]. Authorized users can control real device manipulations and view the run-time status of the controlled device (e.g., a computer numerical control machine) [30].

3.1. Cyber–physical mapping in CPS

The essence of CPS is to add new capabilities to physical systems using computation and communication, which intensively interact with the physical processes [32]. CPS feature tight integration between the 3C in order to provide real-time sensing, dynamic control, and information services for complex systems [33,34]. Compared with DTs, CPS more strongly emphasize the powerful computing and communication capabilities of the cyber world [35], which can enhance the accuracy and efficiency of the physical world. Furthermore, all the CPS architectures that have been proposed by researchers focus on control rather than on mirrored models, whether they are a three-tier [26], five-tier [18,36], or service-oriented architecture [9,37]. As in DTs, feedback loops are important in CPS. Mutual mapping, real-time interaction, and efficient collaboration between the cyber and physical worlds enable the functions of CPS. However, the computational system may affect more than one physical object. For example, a system may include multiple physical components. Therefore, the mapping relationship between the cyber and physical worlds of CPS is not one-to-one, but rather a one-to-many correspondence.

3.2. Digital–physical mapping in DTs

The vision for DTs is to provide a comprehensive physical and functional description of a component, product, or system [27]. The first and most important step is to create high-fidelity virtual models to realistically reproduce the geometries, physical properties, behaviors, and rules of the physical world [22]. These virtual models are not only highly consistent with the physical parts in terms of geometry and structure, but also able to simulate their spatiotemporal status, behaviors, functions, and more [25,38]. In other words, the virtual models and physical entities have a similar appearance, like twins, and the same behaviors, like a mirror image. In addition, the models in the digital environment can

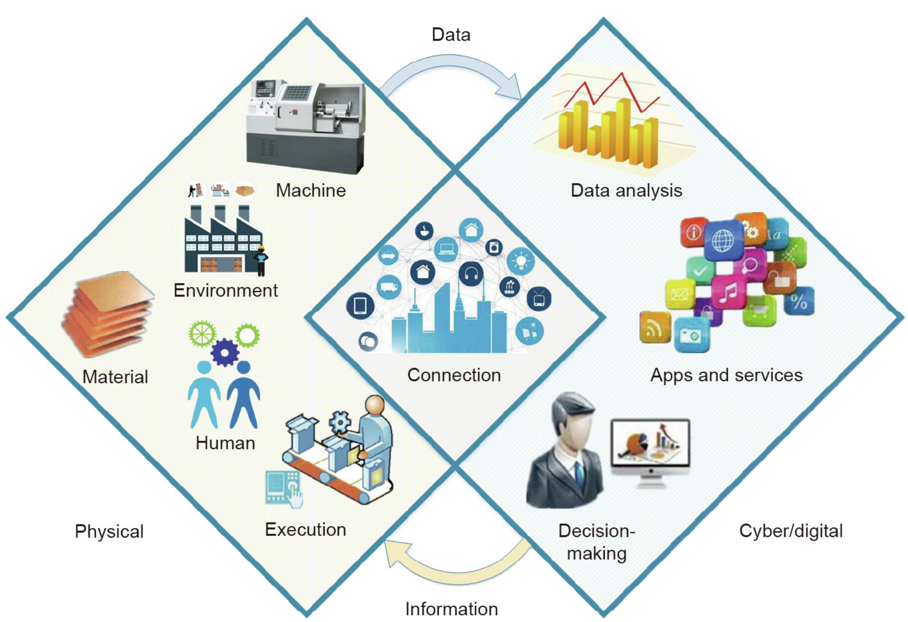

Fig. 2. Mapping between physical and cyber/digital worlds.

directly optimize the operations and adjust physical process through feedback [39]. Using bi-directional dynamic mapping, the physical entities and virtual models co-evolve [19]. Therefore, the mapping relationship between the physical and digital worlds of a DT provides a one-to-one correspondence. A virtual model, which integrates geometry, structure, behavior, rules, and functional properties, represents a specific physical object.

3.3. Control in CPS and DTs

The aim of control is to maintain a system at an acceptable level of operational normalcy in response to disturbances [36]. Control is the core function of CPS and DTs. For example, the cyber–physical interaction of CPS is of key importance [10]. The virtual models and physical processes of a DT co-evolve over the life-cycle of the product or system [40]. The control in CPS and DTs includes two parts: the physical assets or processes affecting cyber/digital representation, and the cyber/digital representation control of physical assets or processes. For the former part of the control, the physical world is dynamic, and the same entity may show different properties at different times [9]. In order to remain consistent, real-time data from the physical world are collected using sensors, and are communicated to the cyber/digital world in order to drive the cyber/digital elements in synchronization with the physical world. Especially for a DT, physical real-time data drive the virtual models in order to simulate the physical process and its evolution [13]. For the latter part of the control, the cyber/digital world uses these data to compute the control output and send it to the actuators for physical implementation [41]. For example, through mathematical models and related computing tools, future statuses and malfunctions can be predicted, allowing better service and control solutions to be generated in advance. As a result, some disturbances, including threats of an unexpected and malicious nature [42], can be eliminated through cyber–physical interactive control.

3.4. Recapitulation

As shown by the concepts described above, both CPS and DTs pave the way for smart manufacturing by forming a closed loop between the cyber/digital and physical worlds based on state sensing, real-time analysis, scientific decision-making, and precise execution. However, by virtue of its virtual models, a DT provides a more intuitive and effective means of improvement in engineering. Through continuous data integration, the DTs' capability of offering related solutions can be strengthened. As shown in Fig. 3, virtual models can be used as a supplement to enrich the composition and functions of CPS, so DT technology can be considered a necessary foundation for building CPS and for opening the way to the realization of CPS. The combination of CPS and DTs would help manufacturers achieve more precise, better, and more efficient management.

4. A hierarchical model of CPS and DTs in manufacturing

Smart manufacturing is a value-creation process from design to production, logistics, and service, in which multiple subjects participate [43]. From the perspective of hierarchy, CPS and DTs can be divided into three different levels according to magnitude: the unit level, system level, and system of systems (SoS) level [44], as shown in Fig. 4 [45].

4.1. Unit level

The unit level refers to the smallest unit participating in manufacturing activities, such as a single piece of equipment (e.g., a machine tool or robot arm), material (e.g., raw material or component with radio frequency identification (RFID) devices or sensors), or even environmental factor [45]. These production elements constitute the physical parts of unit-level CPS and DTs. For example, a machine tool with sensors, actuators, and embedded systems can be considered to be CPS [46] at the unit level. Through data exchange and data processing, a unit-level CPS enables more efficient and resilient machines [47]. Unit-level CPS and DTs share the same physical objects, including equipment, material, and component. Unit-level CPS and DTs can both evolve along with physical machining, assembly, and integration in the process of cyber–physical interaction. However, a unit-level DT must be formed through description and modeling of the geometric shape, identity, and function information, as well as being based on the operating status of unit-level physical objects. Moreover, a DT can perform high-fidelity visual simulation, because a DT focuses more on the construction of models, including geometric shape, rule, behavior, and other constraint models.

4.2. System level

At the unit level, through an industrial network, multiple unit-level CPS or DTs achieve interconnection and interoperability, enabling a wider range of data flow and resources coordination.

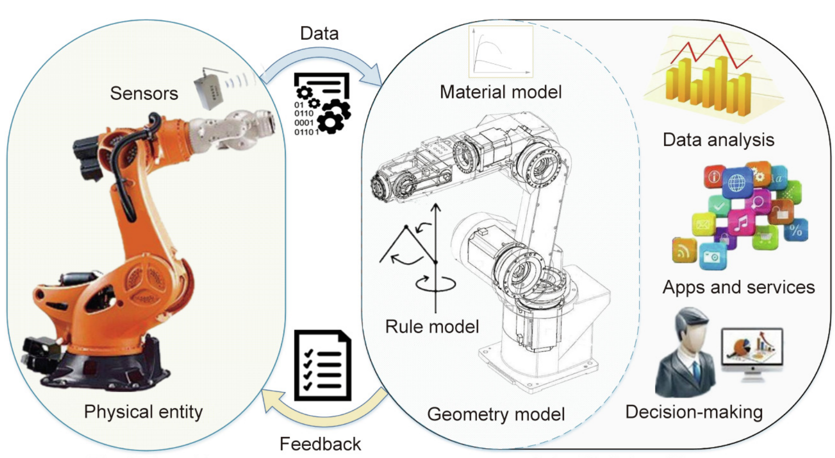

Fig. 3. Integration of CPS and DTs.

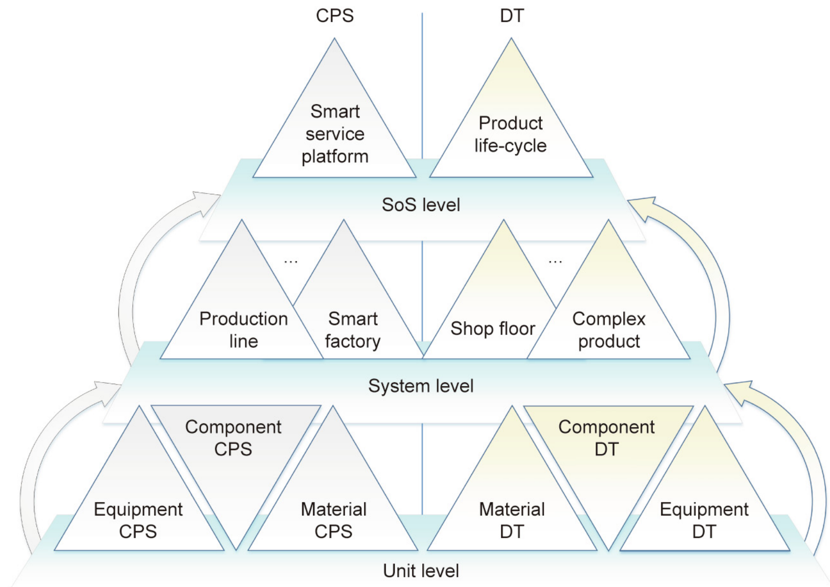

Fig. 4. Hierarchical levels of CPS and DTs in manufacturing [45].

At this level, the integration of multiple unit-level CPS or DTs constitutes a system-level CPS or DT [44]. A production system—which may be a production line, a shop floor, or even a factory—is a system-level CPS or DT. Based on the closed loop of sensing/analysis/decision/execution, a system-level CPS or DT can achieve optimal allocation of manufacturing resources, and can improve the collaboration efficiency among various resources [2,45]. At the system level, CPS and DTs have the same system-level physical manufacturing system (e.g., a production line, shop floor, or factory). The cyber parts of a system-level CPS are not much different from those of a unit-level CPS. However, the virtual models of a system-level DT must be formed through the integration and collaboration of multiple unit-level models [48]. Furthermore, a complex product may be considered to be a system-level DT. For example, for an aircraft consisting of massive components and parts, an engine DT is used to assess the running state and prognose and diagnose damage, while a wing DT is used to evaluate the flight attitude [45]. These correlated DT components are combined to form a complex product DT.

4.3. SoS level

At the system level, cross-system interconnection, interoperability, and collaborative optimization between system-level CPS or DTs can be implemented by constructing a smart service platform. At this level, through the service platform, multiple system-level CPS or DTs form an SoS-level CPS or DT [44]. Compared with a system-level CPS, an SoS-level CPS focuses more on enterprise-wide integration, and even cross-enterprise collaboration [45]. Enterprise collaboration would provide different kinds of cooperation applications, such as commerce cooperation, supply-chain cooperation, and manufacturing cooperation [49]. For example, a collaboration between production, design, and service companies would enable personalized customizations, smart design, remote maintenance, and more. As for a DT, simulation and seamless data transfer from one phase to the next throughout its life-cycle are central [27]. Therefore, an SoS-level DT is an integration of the various stages of the product life-cycle. It brings data from all aspects of the product life-cycle together, which could be useful in various life-cycle phases and even in the next life-cycle [35]. SoS-level DTs lay a foundation for innovative products and quality traceability. For example, the data from manufacturing and maintenance links can also help to improve next-generation design [45]. An SoS-level DT can not only shorten the design cycle, but also greatly reduce the cost in terms of time and money.

4.4. Recapitulation

It is a complex and long-drawn-out process to implement CPS and/or DTs. According to the hierarchical structure, CPS and/or DTs can be implemented in three steps. The first step is to build the unit-level CPS and/or DT. Based on the unit DT, smart monitoring, smart control, and health management of the equipment can be realized. The second step is to build the CPS and/or DT for the system level. Several unit levels can form a system level, which can enable smart production. Finally, based on the unit level and system level, the SoS level is realized.

5. Function implementation of CPS and DTs

Both CPS and DTs are aimed to achieve cyber–physical integration, which is beneficial to smart manufacturing. However, in the implementation of functions, each has its own emphasis. CPS consider sensors and actuators as the main modules, while DTs follow a model-based systems-engineering approach [39] that emphasizes data and models. Both CPS and DTs are inseparable from new IT, which provides their technical basis.

5.1. Function implementation of CPS

CPS integrate 3C technologies to endow physical processes with precise control, remote collaboration, autonomous management, and other functions [10]. CPS are closely coupled with physical processes. Intelligence comes from data. Sensors and actuators are necessary to interact with the physical world for data exchange, which is the most important feature of CPS [46], as they are responsible for sensing the conditions from the physical machines and environment, and executing control commands. As shown in Fig. 5, through multiple sensors distributed on physical devices and in the environment, large-scale distributed data acquisition (e.g., material properties, real-time performance, and environmental conditions) and state identifications are performed to enable the interaction between the cyber and physical worlds [50]. Through data management, processing, and analysis in the cyber world, control commands are generated based on predefined rules and the control semantic specification. The results are fed back to the actuators, which execute operations according to the control commands in order to adapt to changes. The data and control bus provides support for real-time communication and data exchange. With sensors and actuators, any changes in physical process (e.g., behavior, conditions, or performance) cause changes in the cyber world, and vice versa. Therefore, the sensors and actuators can be considered to be the core elements of CPS.

5.2. Function implementation of DTs

The main idea of a DT is to create a digital copy (i.e., virtual models) for physical entities in order to simulate and reflect their state and behaviors through modeling and simulation analysis, and to predict and control their future states and behaviors through feedback [51]. Since the status, behaviors, and properties of the physical world dynamically change, all kinds of data are constantly being produced, used, and stored from the beginning until the disposal of a product [35,52]. The DT integrates whole elements, the entire business, and the process data to ensure consistency [53]. As shown in Fig. 6, models integrating the geometry, structure, material properties, rules, process, and so forth [22] enable the digitization and visualization of the production system and process. Combined with data analysis, a DT enables manufacturers to make more accurate predictions, rational decisions, and informed production [54]. Moreover, in the process of the co-evolution of models and physical processes, the models generate new data. The models serve as a communication and recording mechanism to help interpret the behaviors of machines or systems and to predict their future state based on real-time data, historical data, experience, and knowledge, as well as on data from models. Therefore, models and data can be considered as the core elements of a DT.

5.3. Integration of CPS and DTs with new IT

At present, there is no universal single definition for new IT, although it can be considered as the reciprocity and integration

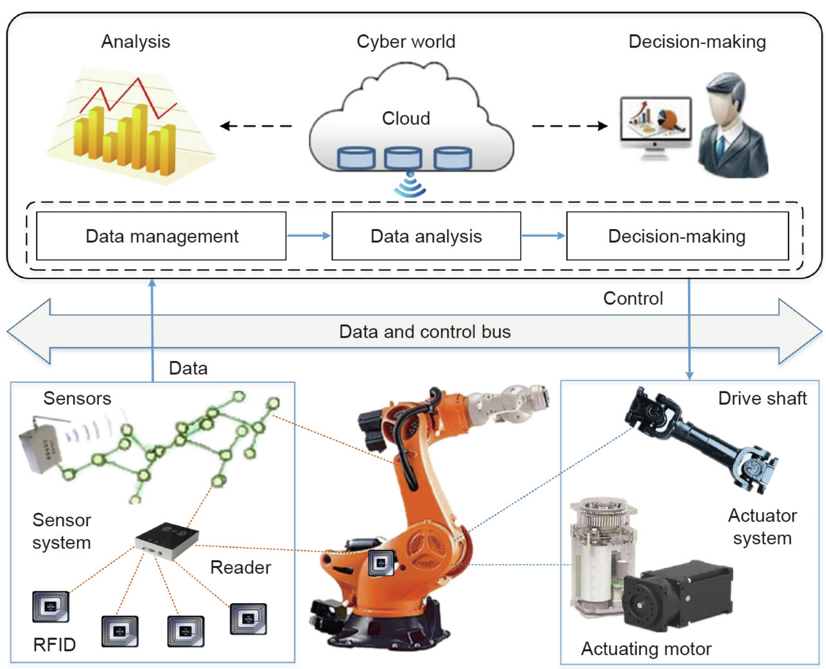

Fig. 5. Sensors and actuators can be regarded as the core elements of CPS.

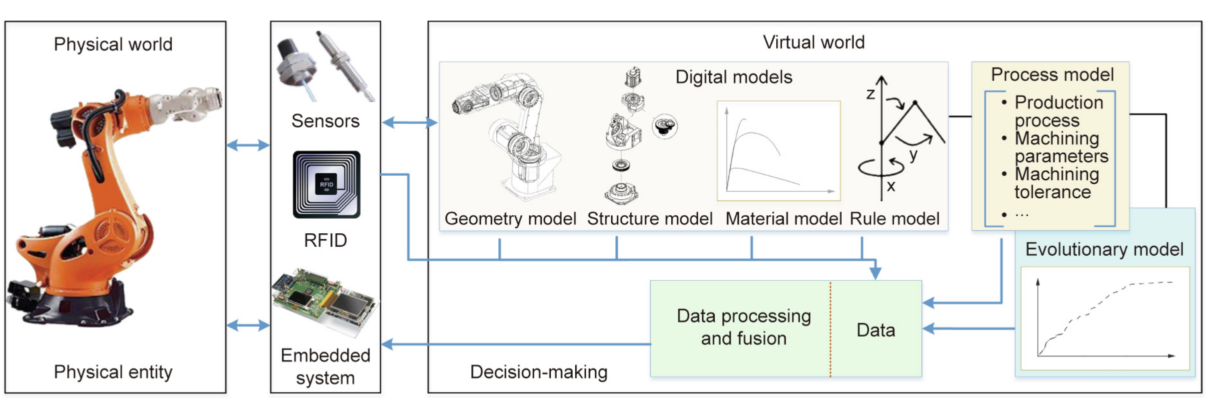

Fig. 6. Models and data can be considered as the core elements of a DT.

of industrial technology, IT, and intelligent technology. New IT is both a vertical upgrade of IT and a horizontal integration of IT with different industries and fields. The IoT, CC, BDA, and AI are the core elements of new IT. In manufacturing, due to digitalization, manufacturing resources that use industrial technology generate a large volume of various kinds of data (Fig. 7) [55]. Because of the IoT, data can be collected in real time to be stored and computed. By uniformly provisioning computing and storage resources, CC can efficiently meet the needs of data computing and storage, while big data technology can effectively mine hidden useful information and knowledge, thus improving the intelligence and better satisfying the dynamic service demands. Thus, the IoT, CC, BDA, and AI play important roles in new IT.

Advances in new IT have had a profound impact on CPS and DTs. First of all, CPS are inseparable from new IT. As enabling technologies, the IoT and cloud-based manufacturing imply signify special CPS in manufacturing, while big data becomes more interesting when applied in CPS [31,56]. Wan et al. [57] believed that CPS are an evolution of embedded computing systems under the architecture of the IoT by means of the introduction of smarter and more interactive operations. Cloud-integrated CPS can open the door to previously unachievable application scenarios to meet the requirements of Industry 4.0 [58]. AI makes the entire system smart, allowing it to "think like people" and "act like people" [59]. As for the DT, it is considered to be a new way of managing the industrial IoT [60]. Integrating cloud technologies in DTs holds promise for ensuring the scalability of storage, computation, and communication [61]. BDA, AI, and corresponding algorithms are also seen as important foundations for a DT. In the exploration of potential DT applications by multiple researchers [62,63], new IT also plays an important role. Compared with CPS, DTs are faster

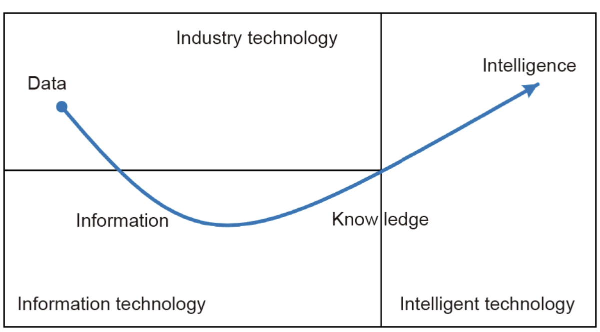

Fig. 7. Integration of industrial technology, information technology, and intelligent technology [55].

and more convenient for integrating new IT. For example, many companies have added new IT to their DT applications, including General Electric, Siemens, PTC, Dassault Systemes, and Tesla [25].

5.4. Recapitulation

The functional implementation of both CPS and DTs aims to endow physical processes with greater efficiency, resilience, and intelligence. Given their respective emphasized elements (i.e., sensors and actuators in CPS, and models and data in DTs), CPS and DTs have different emphasized applications. However, both must integrate with new IT.

6. Correlation and comparison of CPS and DTs

Viewed in a broad sense, CPS and DTs have similar features, and both describe the fusion of the cyber and physical worlds. However, CPS and DTs are not identical. This section provides a correlation and comparison from different perspectives, as described above, along with a brief summary of the end-to-end comparison (Table 1).

As shown in Table 1, CPS and DTs were proposed around the same time. However, the DT did not receive much attention until 2012, when NASA and the US Air Force began to use the DT concept. In contrast, since being proposed by Gill, CPS received attention from academia and governments, with Industry 4.0 listing CPS as its core. Nevertheless, after several years of development, DTs became popular. In comparison, CPS are more akin to a scientific category, whereas DTs are akin to an engineering category. In composition, both CPS and DTs involve the physical world and the cyber world. Through cyber–physical interaction and control, both enable precise and better management and operation of the physical world. However, with respect to the cyber world, CPS and DTs have their respective emphases: DTs focus more on virtual models, which enable the one-to-one correspondence in a DT, while CPS emphasize 3C capabilities, which lead to one-to-many correspondence. In terms of function implementation of CPS and DTs, sensors and actuators enable the interaction between the physical and cyber worlds for data and control exchange. By comparison, models play an important role in a DT to help interpret and predict the behavior of the physical world based on various data. Thus, sensors and actuators can be considered as the core elements in CPS, while models and data are the core elements in a DT. From the perspective of hierarchy, both can be divided into the unit level, system level, and SoS level. However, given that they have different

Table 1
Correlation and comparison of CPS and DTs.

Items	CPS	DTs
Origin	Coined by Helen Gill at the NSF around 2006	Presented by Michael Grieves in a presentation on PLM in 2003
Development	Industry 4.0 listed CPS as its core	Not much attention paid to DTs until 2012
Category	Akin to a scientific category	Akin to an engineering category
Composition	The physical world and the cyber world, CPS focus more on powerful 3C capabilities	The physical world and the cyber world, DTs focus more on virtual models
Cyber–physical mapping[a]	One-to-many correspondence	One-to-one correspondence
Core elements	CPS emphasize sensors and actuator	DTs emphasize models and data
Control	Physical assets or processes affecting cyber representation, and cyber representation controlling physical assets or processes	Physical assets or processes affecting cyber representation, and cyber representation controlling physical assets or processes
Hierarchy	The unit level, system level, and SoS level. A smart production line, shop floor or factory are examples of system-level CPS and DTs; a service platform constitutes SoS-level CPS	The unit level, system level, and SoS level. A complex product can also be considered as a system-level DT; an SoS-level DT covers the product life-cycle
Integration with new IT	Be inseparable from new IT	Be inseparable from new IT. A DT is easier and faster to integrate with new IT compared with CPS

[a] Including two directions—cyber to physical and physical to cyber.

elementary emphases, CPS and DTs have different components on each level. Finally, through integration with new IT, CPS and DTs can enhance the capabilities of manufacturing systems by offering optimized solutions, which contribute to the implementation of smart manufacturing.

7. Conclusions

Smart manufacturing has become an inevitable trend, and achieving cyber–physical interaction and integration in manufacturing is an important prerequisite of smart manufacturing. CPS and DTs are the preferred means to this end. However, these two technologies are not exactly identical. This paper presents a correlation and comparison of CPS and DTs. It reviews and analyzes CPS and DTs from multiple perspectives, and discusses the differences and correlation between them. The comparison from different perspectives that is provided in this work enables a better understanding of CPS and DTs, which appear to be conceptually similar. It also helps to identify the similarities and differences between CPS and DTs, as promising technologies that emphasize cyber–physical integration. Scope remains for further research in both technologies.

Acknowledgments

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Compliance with ethics guidelines

Fei Tao, Qinglin Qi, Lihui Wang, and A.Y.C. Nee declare that they have no conflict of interest or financial conflicts to disclose.

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