Journal of Ambient Intelligence and Humanized Computing (2019) 10:4439–4453
https://doi.org/10.1007/s12652-018-1125-4

ORIGINAL RESEARCH

Digital twin-driven cyber-physical production system towards smart shop-floor

Haijun Zhang[1] · Guohui Zhang[2] · Qiong Yan[2]

Received: 31 March 2018 / Accepted: 2 November 2018 / Published online: 24 November 2018

Abstract
Smart manufacturing is the core in the 4th industrial revolution. Smart shop-floor is one of the basic units of smart manufacturing. With the development of the advanced technologies (e.g. cloud computing, internet of things, model-based definition, advanced simulation, artificial intelligence), a larger number of virtual shop-floors are being built. However, it is very important that how to realize the intelligent interconnection and interaction between physical shop-floors and virtual ones. Digital twin (DT) is one of the key technologies associated to the cyber-physical system. In this paper, we present our vision on the cyber-physical production system (CPPS) towards smart shop-floor at scale via DT. This paper firstly explores a product manufacturing digital twin (PMDT), which focuses on the production phase in smart shop-floor. The proposed PMDT consists of five models: Product Definition Model (PDM), Geometric and Shape Model (GSM), Manufacturing Attribute Model (MAM), Behavior and Rule Model (BRM) and Data Fusion Model (DFM). And then based on PMDT, this paper proposes a new architecture of CPPS, which is composed of five layers (physical layer, network layer, database layer, model layer, application layer). Finally, this paper addresses the opportunities to use DT for the CPPS to support job scheduling during normal operation. Furthermore, the related further work and suggestions are also discussed.

Keywords Smart manufacturing · Cyber-physical system · Digital twin · Production system · Manufacturing service

1 Introduction

Smart shop-floor is one of importance carrier on smart manufacturing, which is the core component of next generation of industrial revolution. In recent years, many manufacturing power countries have made some strategical responses. For example, there are “Industrial Internet” in the USA, “Industrie 4.0” in Germany, “Made in China 2025” and “Industrial Value Chain Initiative” in Japan. In order to achieve the goal of smart manufacturing process, smart shop-floor should be consisted of smart production system, smart products (including workpieces), smart materials, smart operators, smart facilities and so on. The smart shop-floor focuses on the production phase, which includes order planning and job scheduling, production quality, on-time delivery, production method, energy saving, cost, etc.

In the smart shop-floor, the production system should reconfigure the manufacturing resources so as to respond to changing market demands and the status of shop-floor elements (man, machine, material, method, environment) (Wang et al. 2017). The production awareness (e.g., customer orders, raw materials, operators, processes, equipments, environment) and the real-time data analysis should be executed for the optimal decision and the accurate execution. The smart shop-floor is also considered as the “black box”. As shown in Fig. 1, the manufacturing resources come into the smart shop-floor from the left and the bottom of the box, including product design model, manufacturing process, raw material, energy, operators and so on. Meanwhile, smart products and industrial waste come out from the right of the box. However, the physical product may not keep exactly the same of the ideally digital product design model. Because the shop-floor may exist various factors, such as the machining tolerance and the assembling tolerance. Therefore, the traditional digital product design model

✉ Haijun Zhang
zhanghj@zua.edu.cn

1 School of Mechatronics Engineering, Zhengzhou University of Aeronautics, Zhengzhou 450015, People’s Republic of China

2 School of Management Engineering, Zhengzhou University of Aeronautics, Zhengzhou 450015, People’s Republic of China

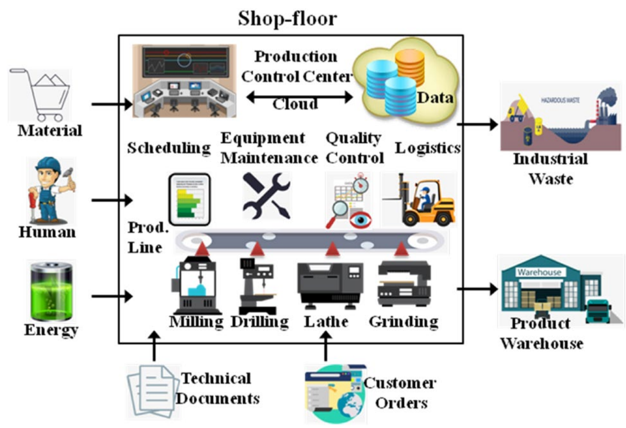


Fig. 1 Overview of smart shopfloor

(also called as digital mock-up, DMU) cannot record and map the real manufacturing process of physical products. If the production system was based on the simulation analysis by using the above product design model, its effectiveness would be significantly limited. Through the traditional production system, it is hard to ensure the production record and form is integral, complete and traceable. For example, the data of the manufacturing bill of material (BOM) and the labor hour is not accurate and not on time in the production system. The development of shop-floor stays in the third stage, namely, there exists the interaction between the physical space and the virtual space, but not complete interaction and communication (Tao and Zhang 2017). With the development of digital manufacturing technology and computer simulation technology, the simulation and evaluation of production process can be carried out in the virtual space. These related works include Digital Factory, Internet of Things (IoT), Cloud Computing, Service oriented Manufacturing System, etc. Despite the significant achievements, existing manufacturing paradigms are insufficient to meet requirements imposed by typical challenges and problems in the shop-floor. These issues are listed as follows.

1. How to interconnect between physical assets and virtual models closely;
2. How to interconnect between virtual models and physical production thoroughly;
3. How to converge the data from real space and virtual space to generate accurate information for production system;
4. How to realize the intelligent production simulation and optimization.

In the complex shop-floor environment, owing to the characteristics of randomness, complexity, heterogeneity, coupling, dynamics of shop-floor elements, there are usually great differences between the real shop-floor and the production system. The existing production system cannot satisfy the reality and timeliness of shop-floor in the virtual space. The production system should need to know the capabilities of the shop-floor elements and their status. In other words, one key of the production system is how to realize the interconnection and interoperability of shop-floor elements between the physical space and the virtual space.

To solve the above issue, Digital Twin, a technology to enhance the interaction between the physical space and the cyber space, has gained wide attentions recently. Digital twin is a core concept of Cyber Physical System (CPS) inspired by "Industrie 4.0". The integrity, completion and traceability of manufacturing process can be realized by CPS. Furthermore, individual skills and talents can be fully realized through cyber-physical production system (CPPS). This is one starting point of our research. The main aims are to provide and enhance transparency in the smart shop-floor and allow real-time production control (Thomas 2016). In summary, the contribution of this paper is to propose an implementation approach of digital twin-driven CPPS towards smart shop-floor especially in the production phase.

The remainder of this paper is organized as follows: Sect. 2 introduces the concept and the application of digital twin and digital thread. In Sect. 3, the product manufacturing digital twin (PMDT) is proposed based on the digital twin and the digital thread. An architecture of digital twin-driven cyber-physical production system (CPPS) is introduced in Sect. 4. Section 5 gives a case study for CPPS in the machining shop-floor of aircraft engine blisk. Section 6 concludes this paper and points out the future research.

2 Digital twin and digital thread

According to the research motivations outlined in the introduction, this section firstly answers the following research questions: "What is the definition of Digital Twin in related literature?" and "What is the application of Digital Twin?"

2.1 Concept of digital twin

The term *Twin* can date back to NASA's Apollo program, in which two identical space vehicles were built (Rosen et al. 2015). One vehicle stayed on earth to simulate the conditions of the other vehicle in the other space. The former vehicle was seen as the twin of the latter one. The twin was used extensively for training during flight preparation. During the flight mission it was used to mirror the flight conditions as precise as possible (Glaessgen and Stargel 2012). It is noted that the twin of space vehicle remains hardware not digital one. Another hardware twin is the "Iron Bird", a ground-based engineering tool used in aircraft industries to incorporate, optimize and validate vital aircraft systems (Airbus Industires 2015). As far as back as 2003, The similar concept of *Digital Twin* was presented by Grieves in one of his presentation about Product Lifecycle Management at the University of Michigan (Grieves 2014). Due to the development of simulation technologies, the idea of twin extended the design phase of product, which leaded to a complete digital model to mirror the physical device along the lifecycle. The term *Digital Twin* was brought to the general public for the first time in NASA's integrated technology roadmap under the technology area 11: Modeling, Simulation, Information Technology and Processing (Glaessgen and Stargel 2012). A *Digital Twin* is an integrated multi-physics, multi-scale, probabilistic simulation of a vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its corresponding flying twin (Shafto et al. 2010). With the emergence of new technologies, Schluse and Rossmann (2016) defined the *Digital Twin* as virtual substitutes of real world objects consisting of virtual representations and communication capabilities making up smart objects acting as intelligent nodes inside the internet of things and services. Other definitions of *Digital Twin* are listed in Table 1. The characteristics of *Digital Twin* are as follows (Boschert and Rosen 2016):

1. To integrate various types of data from physical entity and to map the physical entity faithfully;
2. To exist along the lifecycle of physical entity and evolve with the physical one, and to accumulate knowledge from the physical one;
3. Not only to describe the physical entity, but also to optimize the physical one based on the cyber model.

In this paper, we may consider the shop-floor as a super system, and then investigate the implementation of digital twin in the production system towards smart shop-floor

Table 1 Definition and application object of digital twin

No.	Year	Author(s)	Country	Definition	Object phase	Object level
1	2010	Shafto et al	USA	An integrated multi-physics, multi-scale, probabilistic simulation of a vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its flying twin	Utilization phase	Product
2	2012	Gockel et al 2012	USA	A cradle-to-grave, ultra-realistic model of an aircraft structure's ability to meet mission requirements, which is explicitly tied to the materials and manufacturing specifications, controls, and process used to build and maintain the aircraft	Designing and utilization phase	Product
3	2013	Lee et al	USA	Coupled model of the real machine that operates in the cloud platform and simulates the health condition, which is able to continuously record and track machine condition during the utilization stage	Utilization phase	Product
4	2015	Rosen et al	Germany	Very realistic models of the current state of the process and their own behavior in interaction with their environment in the real world	Production phase	System
5	2015	Bielefeldt et al 2015	USA	Ultra-realistic multi-physical computational models associated with each unique aircraft and combined with known flight histories	Utilization phase	Product
6	2016	Schluse et al	Germany	Virtual substitutes of real world objects consisting of virtual representations and communication capabilities making up smart objects acting as intelligent nodes inside the internet of things and services	Designing phase	Product
7	2016	Schroeder et al	Brazil	Virtual representation of a real product in the context of Cyber-Physical Systems, which can monitor and control the physical entity, while the physical entity can send data to update its virtual model	Lifecycle	Product
8	2016	Kraft 2016	USA	An integrated multi-physics, multi-scale, probabilistic simulation of an as-built system, enabled by Digital Thread, that uses the best available models, sensor information, and input data to mirror and predict activities/performance over the life of its corresponding physical twin	Lifecycle	System
9	2016	Bajaj et al 2016	USA	A unified system model that can coordinate architecture, mechanical, electrical, software, verification, and other discipline specific models across the system lifecycle, federating models in multiple vendor tools and configuration-controlled repositories	Lifecycle	System

especially in the production phase, which is one of contribution of this paper.

2.2 Application of digital twin

Owing to recording the past and present states of product, the application of the digital twin focused primarily on the maintenance, diagnostics and prognostics of equipments, which are the core characteristics of the Digital Twin. For example, Reifsnider and Majumdar (2013) discussed multiphysics stimulated simulation digital twin methods for fleet management. Tuegel (2012) proposed the Airframe Digital Twin for designing and maintaining airframes. Rios et al. (2015) reviewed the different topics of aircraft digital twin, such as product identification, product lifecycle, product information, product configuration, product models, and software applications.

Currently, the digital twin discussion focuses primarily on the design phase, the utilization phase and the product lifecycle (as shown in Table 1). In fact, the research on digital twin in the manufacturing is an evolution of the already ongoing research stream. Digital twin is used to simulate CPS or smart product (Schroeder et al. 2016). For example, the first works reporting research on digital twin in the manufacturing appeared in 2013. In particular, Lee et al. (2013) considered it to be the virtual counterpart of manufacturing resources besides products, which set the basis for a debate about the role of the digital twin in advanced manufacturing environments, such as the envisioned Industrie 4.0 with its core technologies, big data analytics and cloud platforms. Schroeder et al. (2016) proposed the use of AutomationML to exchange data between the digital twin and other systems in the future manufacturing. In 2015, the General Electric Company planned to monitor, diagnose and prognosticate the aircraft engine on the cloud platform (Predix) based on digital twin (Graham 2015). In China, Haier company (2018) employs the digital twin in the "Internet Factory". Tao et al. (2017b) discussed the theory and implementation of the communication and interaction between physical shop-floor and cyber one based on digital twin data. Zhuang et al. (2017) investigated the implementation approach of product digital twin in the phases of product design, manufacturing and service. Monostori (2014) applied the concept of Cyber-Physical Production System (CPPS), which had the potential to achieve a more decentralized way of functioning and interacting. Rosen et al. (2015) pointed out that the digital twin approach was the next wave in modeling, simulation and optimization technology, and then introduced all available product data, which was stored in the digital twin and used for the optimization of the plant's operation.

2.3 Digital thread

Currently, the digital twin technology is moving towards creating a digital representation of a real world object with focus on the object itself (Canedo 2016). However, when each shop-floor element has a digital twin counterpart, the spatio-temporal relations between the objects' digital twins become more valuable than the individual digital twin (e.g., product digital twin, device digital twin, human digital twin). Not only should the production system include various digital twins of shop-floor elements themselves, but also it should include the complex relations among these elements. Rather than locally and individually optimizing systems as it is done today, there will be major efficiency gains when the interactions are optimized at the system level.

Digital thread is an important concept as important as digital twin, which is one of the key technologies towards Industrie 4.0. Digital thread refers to the communication framework that allows a connected data flow and integrated view of the asset's data throughout its lifecycle across traditionally functional perspectives. The digital thread concept raises the bar for delivering "the right information to the right place at the right time". Using digital thread, the interactions among various objects can be available. The actual state and the real-time parameters of physical products would be transferred to their corresponding digital twins in the cyber-physical production system. In such way, it would evaluate the current performance of shop-floor and forecast the future performance dynamically and timely.

At present, the information flow in the production system is one-way, fractional and non-semantic. There's always a lack of effective integration, feedback and traceable in the production system towards smart shop-floor. In this paper, the digital thread is proposed to integrate various production segments (detailed in the next section). The information among production segments would be identified and formatted. The related standards and tools of information exchange could be developed through digital thread. The digital thread will be applied to build PMDT in the third section.

3 Product manufacturing digital twin (PMDT)

This section proposes a product manufacturing digital twin (PMDT) for CPPS towards smart shop-floor. A general and standard model for digital twin (DT) was first built by Grieves (2014) (Fig. 2), which can be depicted as in the following expression: DT = (PP, VP, VR) where PP refers to physical products in Real Space, VP refers to virtual products in Virtual Space, and VR refers to the connections of data and information that ties the virtual and real products together.

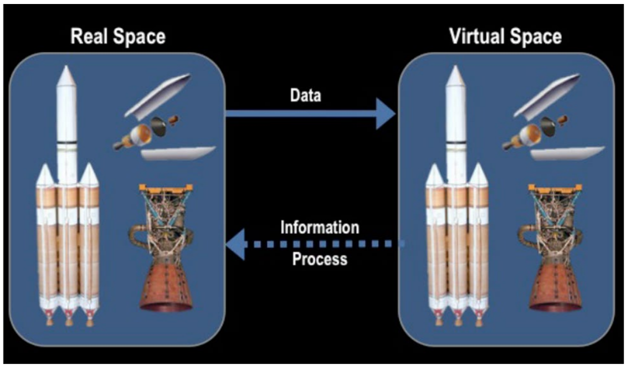


Fig. 2 Digital twin model

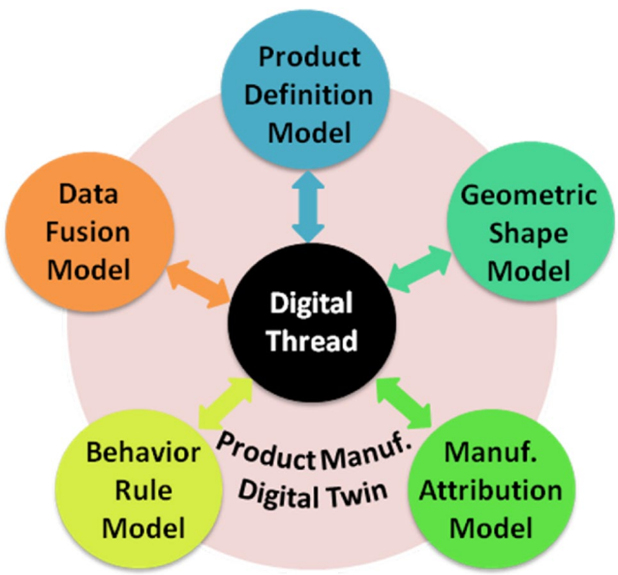


Fig. 3 Basic components of DTPM

In order to describe the complex shop-floor elements and their relationships digitally, the proposed PMDT consists of five kinds of models: Product Definition Model (PDM), Geometric and Shape Model (GSM), Manufacturing Attribute Model (MAM), Behavior and Rule Model (BRM), Data Fusion Model (DFM), as shown in Fig. 3. VP = (PDM, GSM, MAM, BRM, DFM), is a high fidelity digital model of PP, which integrates multiple variables, scales and abilities of PP to reproduce its geometries, physical properties, behaviors and rules in Virtual Space.

1. *Product definition model (PDM)* The product definition information includes the product design and manufacturing information, such as 3D annotation and dimensions, bill of material (BOM), geometric tolerances, surface finish, material specifications, etc. These information is conveyed through an integrated 3D model, which is called product definition model (PDM) in this paper. In order to guarantee the uniqueness of product data, there is no 2D engineering drawing in the smart shop-floor except PDM.
2. *Geometric and shape model (GSM)* It is concerned with the geometric dimensions and shape of the smart shop-floor elements, such as the height/width/length, horizontal/vertical and single-spindle /multi-spindle of machine tools, the monocrystal/polycrystal of materials.
3. *Manufacturing attribute model (MAM)* It is concerned with the non-geometric attributes of the smart shop-floor elements (except products), including function, process, energy consumption, cost, quality, quantity etc. Take a machining center for example, the turning, milling and drilling can be used in this machining center, whose repositioning precision is 0.005 mm, and production cost is 25 RMB/s. To find appropriate manufacturing resource for the bottleneck processes, there will be a match between resource requirements and attributes.
4. *Behavior and rule model (BRM)* It is concerned with the behavior and rule of smart shop-floor elements. The behavior includes activities, movements, reactions, actions of operators and equipments in the smart shop-floor. For example, the behavior factors of machine tool include: standby, running, breakdown, out of service, etc; the behavior factors of operator include: tool setting, emergency shutdown, clamping workpieces, measuring workpieces, cleaning clips, etc; the behavior factors of material include: pre-inspection, qualified, unqualified, return, etc. To formally describe these behavior factors and the relationship between them, the behavior model can be built by Unified Modeling Language (Schütz et al. 2012), Petri Net (Moore and Gupta 1996), etc. And the rule types include process constraints, capacity constraints, material constraints, spatio-temporal constraints, energy consumption constraints, etc. The rule is modeled to describe the domain knowledge and support manufacturing decisions (Wiers 1996; Guerra-Zubiaga and Young 2006), which can make the behavior model be capable of evaluating, optimizing and predicting. To build the rule model, these technologies can be employed, such as mathematical programming (Choi and Choi 2002), Pareto optimization (Moncayo-Martínez and Recio 2014), fuzzy logic (Fortemps 1997), robust optimization (Tjornfelt-Jensen and Hansen 1999), neural network (Noorul Haq and Radha Ramanan 2006), etc.
5. *Data fusion model (DFM)* Includes the description and network modeling of the associated relationships that exist between production data, such as the complex networks theory (Li et al. 2017). In the smart shop-floor, the multi-source data needs to be dynamically acquired, combined and turned into comprehensible knowledge.

Therefore, the knowledge would be mined and the relationship among tacit knowledge would be found. In such way, the uniqueness and authority of PMDT could be guaranteed under the spatio-temporal dynamic evolution. With the development of intelligent manufacturing technology, the data generation methods are expanding. The relationship between data has become inextricably linked, showing the situation of large-scale data association, crossover and integration. For example, the worker, equipment, cost and delivery will vary according to manufacturing process route in the real shop-floor. To mine information and knowledge from mass shop-floor data, there needs a data fusion model, including the following key technologies: (1) schema/ontology alignment technology; (2) entity linking technology; (3) conflict resolution technology; (4) relation inference and evolution. Data fusion and mining will be effective to solve production problem in shop-floor, such as artificial neural networks (Yildirim et al. 2006), support vector machine (Rostami et al. 2015), manufacturing big data (Tao et al. 2018), deep learning (Wang et al. 2018a, b).

Compared with Grieves' model, the proposed models fuse data from both the physical and virtual aspects for more comprehensive and accurate production information. The proposed models focus on production phase rather than the final product in shop-floor, where is different from Grieves' model. The proposed five models are coupled in functions and structures to form a complete mirror image of the production process.

1. The structural mirror can present an intuitive graphical interface for users to view and set some parameters. When the physical assets change in Real space, the corresponding digital twins also follow these changes in Virtual Space to keep high fidelity. For example, two identical space vehicles were built in the NASA's Apollo program. One vehicle stayed on earth to simulate the conditions of the other vehicle in the other space. The former vehicle was seen as the twin of the latter one. The twin was used extensively for training during flight preparation. During the flight mission it was used to mirror the flight conditions as precise as possible (Glaessgen and Stargel 2012). Another example, the General Electric Company planned to monitor, diagnose and prognosticate the aircraft engine on the cloud platform (Predix) based on digital twin (Graham 2015).
2. The functional mirror can encapsulate the functions of manufacturing resources as services for unified management and on-demand usage. For example, single manufacturing task specifies the manufacturing system has to search out all the manufacturing services qualify for its function requirements and select the optimal one to execute it, while on multiple manufacturing task, the manufacturing system has to invoke several manufacturing services in a certain sequence and construct a composite resource service to execute it (Tao et al. 2012).

As shown in Fig. 4, there is a production line in the smart shop-floor. Each workstation consists of operators, equipments, materials, environment and technical specifications. The transformation of the energy form occur when the workpieces and materials are moved among the workstations. In the research and development phase, the parameters are passed from the simulation optimization model to the PDM. When a physical product enters the physical shop-floor, an instance of PDM is generated in the virtual space. Likewise, an instance of GSM, MAM, BRM and DFM is

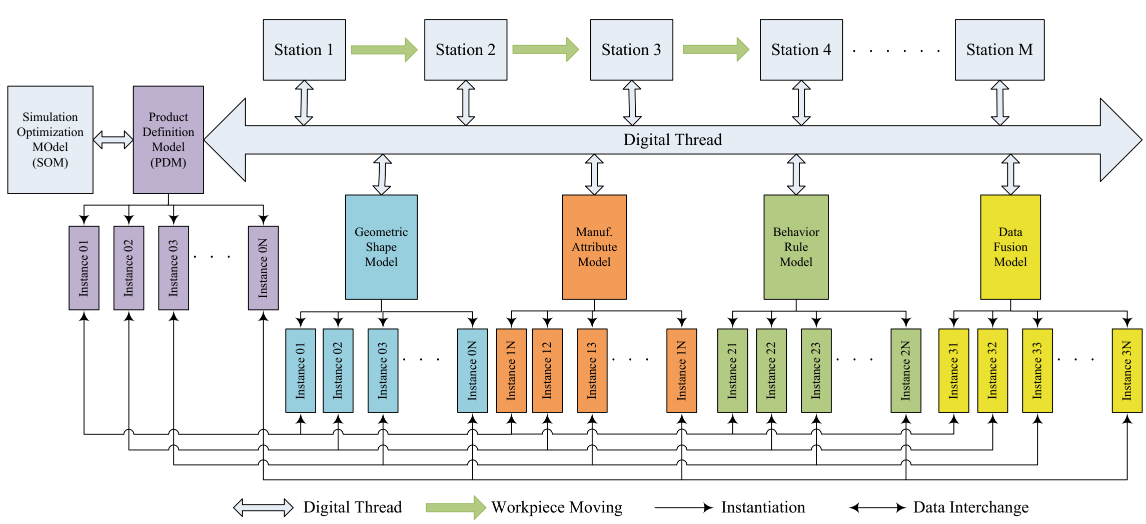


Fig. 4 Diagram of PMDT in smart shopfloor

generated respectively. The proposed PMDT is composed by five kinds instances based on digital thread and digital twin. With the movement of physical products, the corresponding processing, assembly and quality inspection procedures are completed in the physical space. In the virtual space, the five instances of each product are updated through digital thread, which realizes the unification of product between the physical space and the virtual space. In order to optimize design, a large number of instances of PMDT can be statistically generalized and transferred to the simulation optimization model through digital thread. Finally, the PMDT is a unique, reversible, faithful model of the corresponding physical product in the virtual space.

As mentioned above, the PMDT can record and map the manufacturing process of physical products truthfully. Therefore, the PMDT is very important to the cyber-physical production system for smart shop-floor. As shown in Fig. 4, the PMDT integrates the data of physical product lifecycle, especially the production phase. In the smart shop-floor, the PMDT supports the seamless integration and synchronization of the digital manufacturing and measurement system through the embedded CPS, which allows us to verify the product manufacturing process in the virtual space (Fig. 5). Meanwhile, the PMDT would provide the production models and the production data (including historical data and current data) for the shop-floor simulation. Whereas, the shop-floor simulation results can also be predicted and evaluated through PMDT. Based on PMDT and shop-floor simulation, smart shop-floor services can be provided, such as shop-floor evaluation, shop-floor analysis, shop-floor optimization and so on. In the physical shop-floor, the production information would be provided to schedulers, warehouse workers, operators, inspectors, researchers involved, while the PMDT can also provide the authoritative production information to salesmen, accountants, service engineers, besides the above personnel.

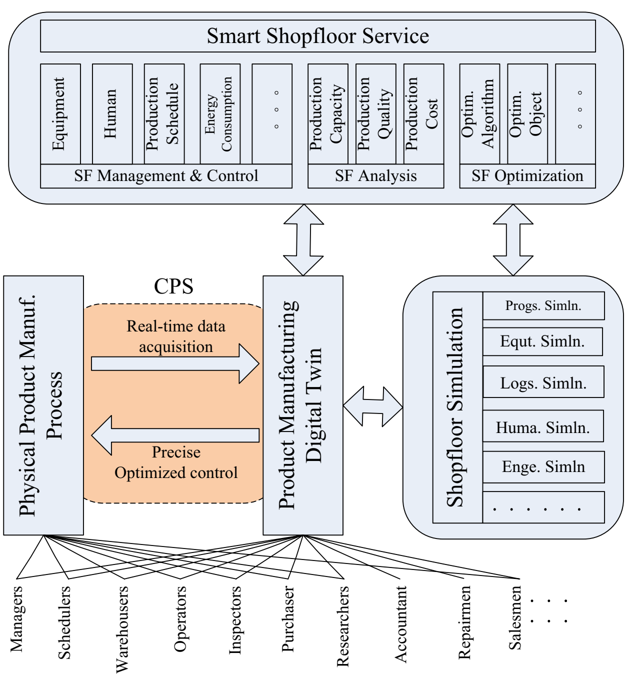


Fig. 5 Application of DTPM for CPPS

4 Digital twin-driven cyber-physical production system

The section answers the following research questions: "What is the architecture of digital twin-driven Cyber-Physical Production System (CPPS)?" and "What is the role of digital twin in CPPS?"

In 2015, German Commission for Electrical, Electronic and Information Technologies of DIN and VDE (DKE) published a Reference Architecture for Industrie 4.0 (RAMI 4.0) (ZVEI 2015), as shown in Fig. 6. The technical framework (ISA-95) and standards (IEC62264/61512/62890) are employed in RAMI 4.0; however, there is a long way to apply it in the manufacturing practice. Therefore, this paper proposes a new reference architecture for smart shop-floor, which is a reusable integration of components engineered to facilitate development and deployment for enterprises. Since the proposed architecture is a weak-coupling structure, the dependency between layers is downward, and the bottom is "ignorant" to the upper layer, the change of the upper layer has no effect on the bottom. This is also an advantage of the proposed architecture. As an industrial reference of digital twin, this paper proposes an architecture of digital twin-driven CPPS, which consists of five layers as follows (Fig. 7):

Physical Layer Refers to physical entities in the shop-floor, e.g., machine tools, Automated Guided Vehicles (AGV), robots, workers, parts, sensors, Radio Frequency Identification (RFID), materials, etc. The physical entities

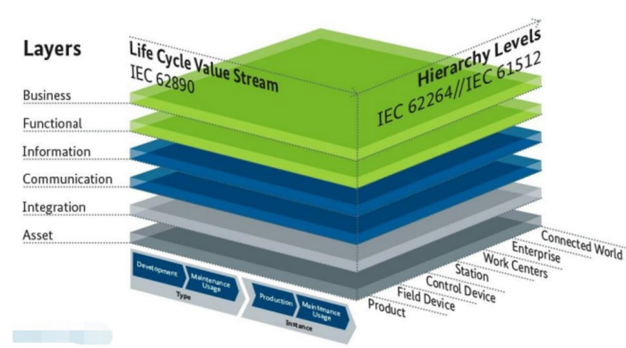


Fig. 6 RAMI 4.0

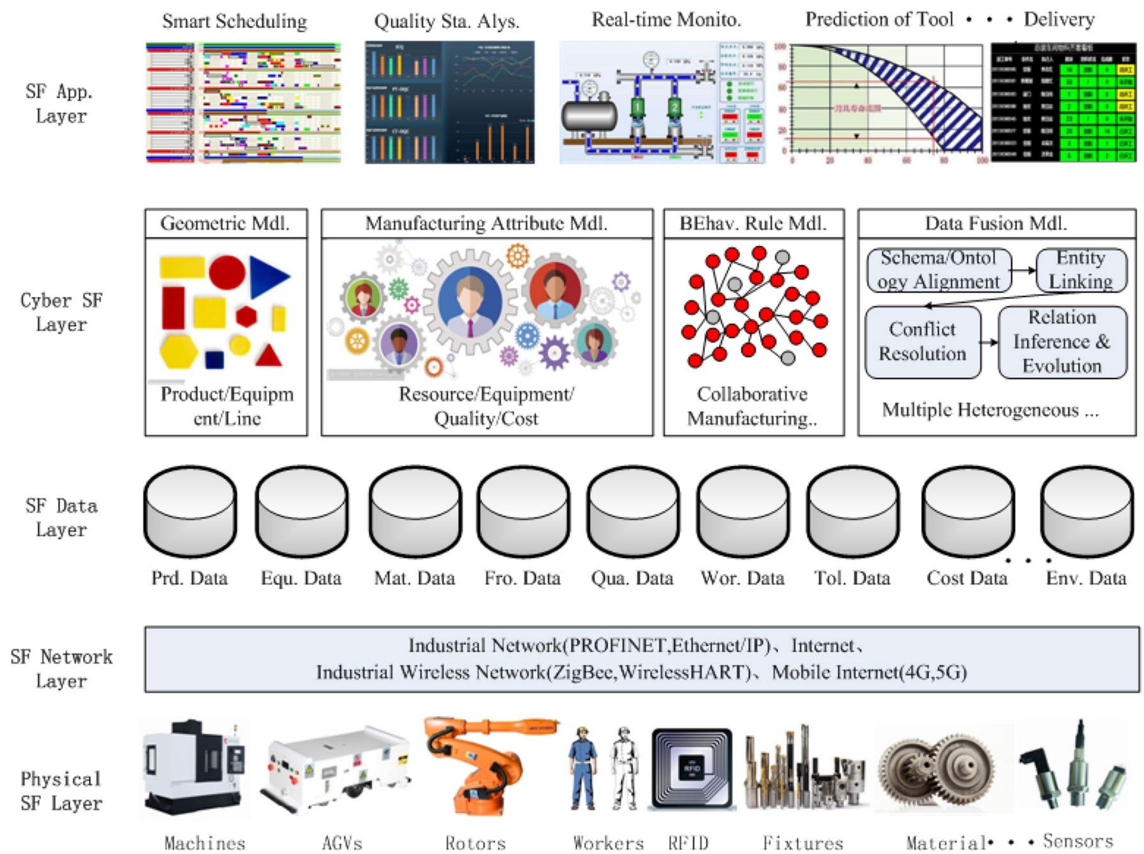


Fig. 7 Architecture of digital twin-driven CPPS

can accept manufacturing instructions and perform manufacturing tasks. For example, Distributed Numerical Control (DNC) can realize: (a) transfer NC code; (b) collect and upload the machine status; (c) transfer the tool data; (d) manage and trace NC code. In addition to the common functions of the shop-floor, this layer can perceive and treat the heterogeneous, multi-source, real-time data based on the Internet of Thing (IoT). For example, various sensors should be installed in smart shop-floor, such as temperature sensor, voltage sensor, pressure sensor, speed sensor, displacement sensor and laser sensor. As a result, the data sources and data formats might not be exactly. If AGV (electromagnetic, laser, magnetic belt) encountered obstacles, it needs to stop and/or reroute in time.

Network Layer Refers to the network infrastructure, which is the bridge between the physical space and the virtual space. These technologies include Industrial Internet, Industrial Ethernet, Industrial Wireless Network, Mobile Internet (5G), etc. The network employed in this layer focuses on reliability, real time and convenience. In the physical layer, there are much heterogeneous and multi-source of shop-floor data. The isomorphism should be carried out towards the network topology and protocol among various heterogeneous systems. The unified interfaces should be provided to access heterogeneous systems identically in this layer. For example, the wireless Internet of Things technology of shop-floor includes: Bluetooth, WIFI, Zigbee, RFID, 4G/5G, Profinet, etc. The technology of shop-floor field bus includes Profibus (Germany), P-Net (Denmark), WorldFIP (France), etc.

Database Layer Includes production data, tooling data, equipment data, material data, quality data, cost data, human data, environmental data, etc, which are the base of digital twin-driven CPPS. Owing to the network technology and the sensor technology, the shop-floor has a tendency of Big Data "3V" characteristics, namely Volume, Variety, Velocity (Qi and Tao 2018). This layer focuses on not only the efficiency, visualization of data processing, but also the seamless connection of multi-source and heterogeneous data. For example, the semistructured data (e.g., equipment maintenance orders) and unstructured data (e.g., part drawings) can be stored in Hadoop Distributed File System. In shop-floor, the data in various production systems (e.g., MES, ERP, WMS, etc) is structured. The structured data can be exported by Sqoop from the relational databases (e.g., Mysql, SQL Server, Oracle, Sybase, DB2) to Hbase. Mahout allows for the distributed processing, analysis and mining of the data in Hbase through the principal component and cluster analysis.

Model Layer It is very important layer to digital twin driven CPPS, which consists of various models, e.g., Production Definition Model (PDM), Geometric and Shape Model (GSM), Manufacturing Attribute Model (MAM), Behavior and Rule Model (BRM), Data Fusion Model (DFM). PDM can employ Model-based Define (MBD) technology (Virgilio et al. 2010), which has been applied in Boeing 787. There has been a lot of mature 3D modeling technology for GSM, such as Unigraphics NX, Inventor, Solidworks,PTC Creo. The technology for MAM includes XML, Ontology and so on. The technology for BRM includes STEP, UML, IDEF, Petri Net, and so on. The key technology for DFM includes schema/Ontology alignment technology, entity linking technology, conflict resolution technology, relation inference and evolution.

Application Layer Including various services of the production system, which are response for decision support, e.g., job scheduling optimization, real-time monitoring of manufacturing resources, quality management, tool life prediction, material delivery optimization, etc.

5 Case study for digital twin-driven cyber-physical production system

5.1 The procedure of job scheduling based on digital twin-driven CPPS

This procedure is based on the architecture of digital twin-driven CPPS, which can provide the real-time data acquisition and dynamic optimization. In this section, the shop-floor job scheduling optimization is chosen as the application of digital twin-driven CPPS. Therefore, this procedure includes as follows (Fig. 8):

Step 1 In the physical shop-floor layer, the production data would be acquired through the IoT, which is also called as shop-floor big data. These huge amounts of data would be managed and stored in the shop-floor data layer. When each physical product (or workpiece) starts to enter the physical shop-floor, an instance of PMDT is generated in the virtual space. This PMDT will accompany the product lifecycle, such as production phase, maintenance phase and recovery phase, etc.

Step 2 According to the real-time data in the shop-floor data layer, the models (PDM, GSM, MAM, BRM, DFM) construct a mapping between the physical shop-floor and the virtual one. Each instance of PMDT can record all important information of products, such as machine number, cutting parameters (cutting speed, cutting depth, feed rate), tool number. These data can also be used for the dynamic optimization of the shop-floor (Fig. 5). For example, the tool life can be optimized through the CPPS, if the tool wear was predicted.

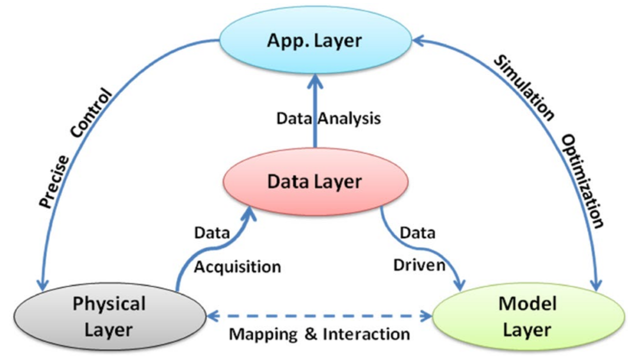


Fig. 8 Scheme of digital twin-driven CPPS

Step 3 In the shop-floor application layer, intelligent algorithms, such as genetic algorithm (Yu and Yin 2010), differential evolution algorithm (Zhang et al. 2016), simulated annealing algorithm (Baykasŏglu 2006), can be employed to optimize the scheduling in the smart shop-floor. The optimization results would be provided to the shop-floor planners graphically and digitally. It is noted that the shop-floor planners should choose an optimization result for the final order, which would be received in the physical shop-floor layer through the IoT.

Step 4 When there was failure in the physical shop-floor, e.g., equipment breakdown, material shortage, urgent orders, the shop-floor data layer would pick up these kinds of abnormal information, and then the real-time status of PMDT would be updated in the model layer.

Step 5 In the shop-floor application layer, intelligent algorithms can be employed to optimize the models again. The optimization results would be provided to the shop-floor planners to decide wheather reschedule or not. If yes, the new scheduling would be transferred to the physical shop-floor through the IoT.

As above mentioned, the more accurate and real-time information can be provided to the shop-floor planners based on the digital twin-driven CPPS. Therefore, the shop-floor planners can reduce the workload and get the optimal resource allocation.

5.2 Case study

This section takes the blisk machining as an example. The aircraft engine manufacturing is an extremely complex system engineering. One of the important parts of aircraft engine is "blisk", which works in the extreme enviroment. For aircraft engine, the blisk machining can take a substantial amount of time. Owing to the integrated design of blades and roulette, the blisk greatly simplifies the structure of aircraft engine. In the top of Fig. 9, the physical blisk manufacturing starts from the raw material, to work in progress (WIP) and then to the finished product. In the bottom of Fig. 9, it is an instance of PMDT corresponding to the physical blisk in the virtual space. In the middle of Fig. 9, the smart shop-floor consists of the physical shop-floor and the virtual shop-floor. All shop-floor activities focus on the blish machining. Consequently all available data from the physical product in the smart shop-floor is stored in the PMDT and used for the scheduling optimization via the CPPS. According to the proposed models and architecture, the case of blisk machining shop-floor is illusurated as follows:

At Physical Layer, in this case, there are six machine tools (M1, M2, M3 …), sensors and products (e.g., raw material, work-in-progress) etc in the blisk machining shop-floor. Different kinds of sensors are used to collect the operating information and dynamic signals in the machining progcess.

At Network Layer, the equipment status information is uploaded to the equipment database (Data Layer) by the wired or wireless network communication technology (Network Layer), such as ProfiNet, ZigBee, WirelessHART, Internet, 4G/5G.

At Data Layer, in this case, the types of status (e.g., in-use, available, out-of-service) and when the status changes can be acquired, as shown in the 3rd column of Table 3. The maintenance time of machine tools can be forecasted (Khatami and Zegordi 2017), as shown in the 4th column of Table 3. Various production progress data can be acquired from the physical layer via SCADA and MES, such as the quantity, quality and machining time of parts. When the machine tools (M1, M4, M5) broke down (namely Scene 3 in Table 3) with regard to the scheduling scheme b (Fig. 11b), two processes (O11, O12) had been finished for

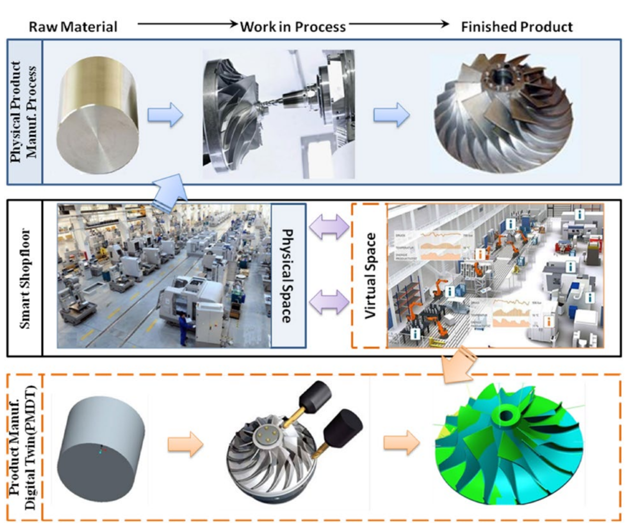


Fig. 9 Example of digital twin-driven CPPS

Workpiece J1, while there was an unfinished process (O13); no process had been finished for Workpiece J2, while there were three unfinished process (O21, O22, O23); only one process (O31) had been finished for Workpiece J3, while there were two unfinished processes (O32, O33); The processes of Workpiece J4 were not affected, since the process (O41) was assigned to the machine tool (M3).

At Application Layer, in this case, smart job scheduling is chosen as an application example based on digital twin-driven CPPS. For one thing the proposed PMDT can present an intuitive graphical interface for users to view and set some parameters, for another the proposed PMDT can provide the unique and authoritative data under the spatio-temporal dynamic evolution in shop-floor. The authoritative data is important for job scheduling optimization, such as equipment data, production progress data, etc. And then CPPS can employ intelligent optimization technology (e.g., genetic algorithm, particle swarm optimization, tabu search, ant colony algorithm, etc), in order to reschedule all unfinished processes at an overall level.

At Model Layer, in this case, GSM includes a set of digital three-dimensional (3D) models of manufacturing resources except products, such as machine tools, robots, Automated Guided Vehicles (AGVs), production lines, workers, raw materials and so on. Combining 3D models of machine tools (Model Layer) and the real-time status data (Data Layer), the more intuitionistic and realistic environment of shop-floor can be simulated. The operators can learn that a comprehensive understanding of machine tools in Virtual Space, which is of great value of manufacturing applications and services (Application Layer), such as job scheduling.

At Model Layer, in this case, PDM refers to the blisk design and manufacturing information, such as 3D annotation and dimensions, bill of material (BOM), geometric tolerances, surface finish, and material specifications, etc. It should be noted that these information will be conveyed through an integrated 3D model. Combining 3D models of products (Model Layer) and the production process data (Data Layer), the more intuitionistic and realistic environment of shop-floor can be simulated. The managers can learn that a comprehensive understanding of production in Virtual Space, which is of great value for job scheduling (Application Layer).

At Model Layer, in this case, BRM refers to the process route that is important to job scheduling optimization, since the route needs to be closely followed. As shown in Fig. 10, there are four kinds of process routes of blisk. Only key processes are selected as the scheduling object, which are displayed in Yellow. Because these equipments are key to production in shop-floor, and their quantity are relatively limited. These processes in Yellow are defined as bottlenecks (Joseph et al. 1988). To optimize the bottlenecks after

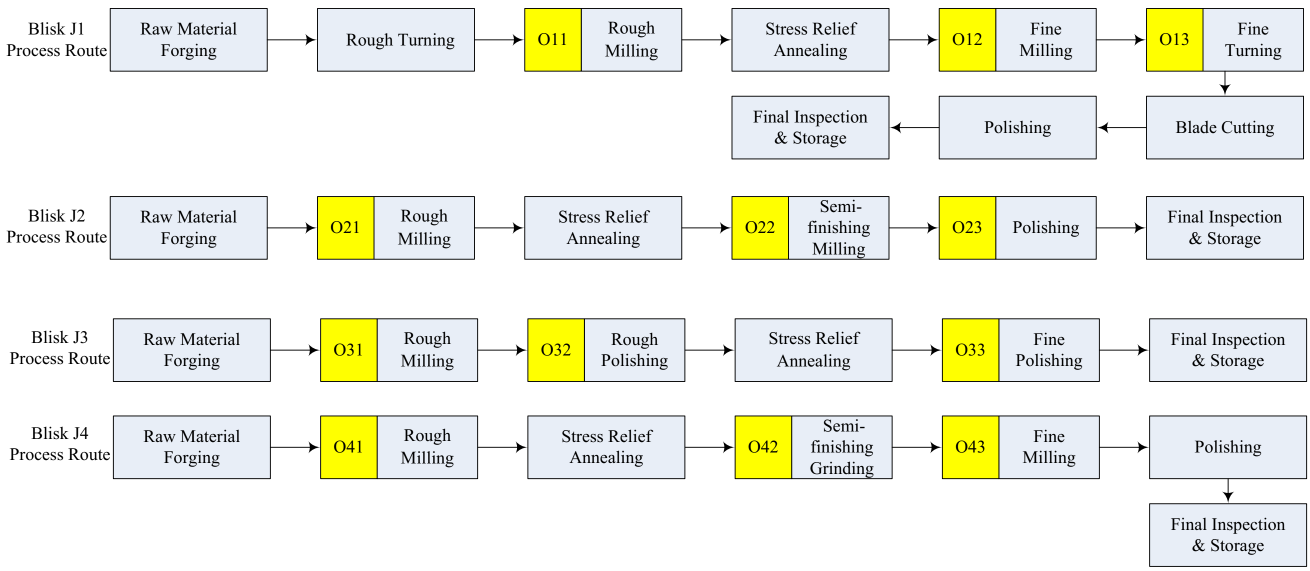


Fig. 10 Process routes of blisk

machine failure is the goal of this case, as is an application example of CPPS.

At Model Layer, in this case, MAM includes data modeling of the non-geometric attributes of manufacturing resources, such as fucntion, process capability, accuracy, cost and location and so on. Take a machine tool for example, its function includes turning, milling and drilling.

At Model Layer, in this case, DFM includes the description and network modeling of the associated relationships that exist between production data. Firstly, the shop-floor operating parameters (e.g., equipment status, plan implementation), and shop-floor performance parameters (e.g., product quality, delivery time) will be converted to the standard data. The associated relationships can be identified by cluster analysis and sequential pattern algorithms. The shop-floor performance evolution could be found by data mining, which is to establish prediction model of shop-floor performance. Take the traditional method of job scheduling for example, (1) analyzing the relationships between scheduling parameters and objectives to obtain the optimal scheduling scheme, (2) establishing the mathematic model to describe the specific scheduling problem, which includes problem constraints, optimal objectives and so on, (3) designing intelligent algorithms to solve the mathematic model, according to the specific scheduling problem (Zhang et al. 2009). However, with the variety and timeliness of customer demand, the traditional method is no longer suitable for job scheduling problem in smart shop-floor (Li et al. 2016). Data fusion and mining will be effective to solve job scheduling problem.

In this case, the process time of each operation is different to each machine (the first item of Manufacturing Attribute Model, 1st item of MAM), which is listed as in Table 2. The 1st column refers to the index of workpieces to be operated; the 2nd column refers to the index of operations; the process time corresponding to every machine locates from the 3rd to the 8th column. The symbol refers that the operation could not be handled at the corresponding machine. In order to simulate the failure in the physical shop-floor, this paper provides 3 scenes (the second item of manufacturing Attribute model, 2rd item of MAM), as shown in Table 3. The 1st column refers to the index of failure; the 2nd column refers to the index of fault machine; the 3rd column refers to the point of failure; the 4th column refers to the predicted maintenance time of machine.

According to Step 3 in Section A, two scheduling schemes are got in the shop-floor application layer, which are shown in Fig. 11. Take Scene 3 for example, these machines M1, M4 and M5 break down at the point 5o'clock, which are shown in Table 3. With regard to Scheme (a) shown in Fig. 11a, if the Right Shift (RS) strategy was employed, the operation O32 and O33 would be delayed and the final completion time should be 23 time unit in Fig. 12. However, if the proposed CPPS was employed for scheduling, the final completion time would be 19 time unit in Fig. 13. With regard to Scheme (b) shown in Fig. 11b, the final completion time would be 23 time unit using the RS strategy, which is shown in Fig. 14. However, the completion time should be 18 time unit using the CPPS, which is shown in Fig. 15. The comparative result is shown in Table 3. Two performance functions are employed: one (*f1*) is to minimize the maximum completion time, and the other (*f2*) is to minimize the difference between before and after scheduling. As seen in Table 4, the proposed CPPS is superior to the RS. The

Table 2 Case for 1st item of MAM

Workpiece	Process	Canditated machines and process time					
		M1	M2	M3	M4	M5	M6
J1	O11	2	3	4	–	–	–
	O12	–	3	–	2	4	–
	O13	1	4	5	–	–	–
J2	O21	3	–	5	–	2	–
	O22	4	3	–	–	6	–
	O23	–	–	4	–	7	11
J3	O31	5	6	–	–	–	–
	O32	–	4	–	3	5	–
	O33	–	–	13	–	9	12
J4	O41	9	–	7	9	–	–
	O42	–	6	–	4	–	5
	O43	1	–	3	–	–	3

Table 3 Case for 2rd item of MAM

Scene	Fault mach.	Fault Time.	Maint. Time
1	M6	5	4
2	M2	11	5
	M3	11	3
3	M1	5	2
	M4	5	6
	M5	5	1

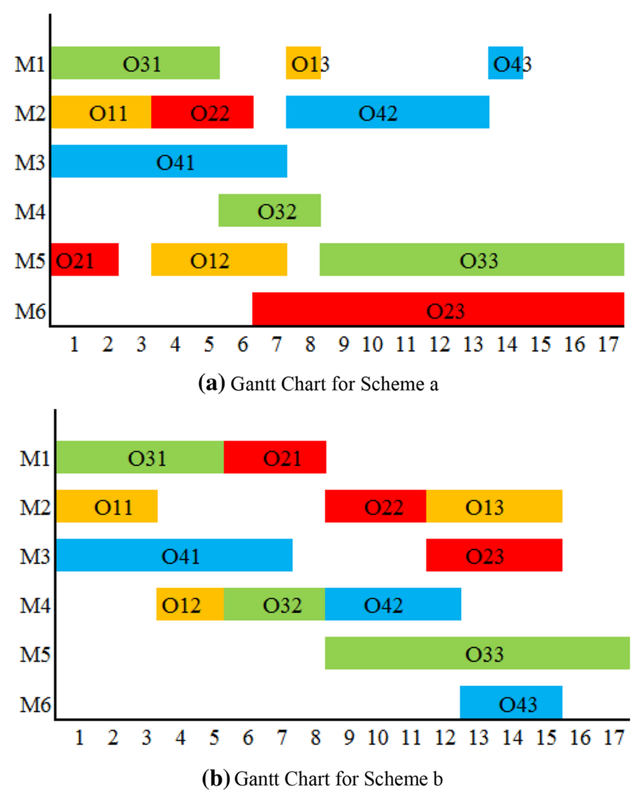


Fig. 11 Gantt charts for two initial schemes

completion time *f1* using the CPPS is not greater than that using the RS. With regard to Scene 2, Scheme (a) is superior to Scheme (b). Because *f2* is equal to 0 for Scheme (a) using the CPPS, while *f2* is equal to 1 for Scheme (b) using the CPPS in Scene 2. With regard to Scene 3, Scheme (b) is superior to Scheme (a). Because *f2* is equal to 2 for Scheme (a) using the CPPS, while *f2* is equal to 1 for Scheme (b) using the CPPS in Scene 2.

In this case, the proposed CPPS is driven by the physical manufacturing resources and the corresponding virtual PMDT. And then the remote, real-time monitoring of physical equipments is realized. The real status of physical equipments is transparent and interpretable by means of PMDT, such as the timely warning for abnormal case, process time and manitenacne time. The application effect of PMDT can be proved in the case study as follows:

1. The uniqueness and authority of product manufacturing data could be guaranteed in dynamic shop-floor, in order to generate accurate information for production system.
2. The real status of manufacturing resources is transparent and interpretable.
3. The CPPS is able to improve production efficiency of shop-floor.

6 Conclusion

In the context of smart manufacturing, smart shop-floor is a major topic. The production system should react autonomously on various disturbances in smart shop-floor. The technology of Digital Twin enables exactly the above production system, because all models and data are available consistently. This paper has just begun to study on Digital Twin in manufacturing industry. The main contributions are concluded as follows: (1) the concept and basic

Fig. 12 Gantt chart for scheme a (scene 3) using the RS

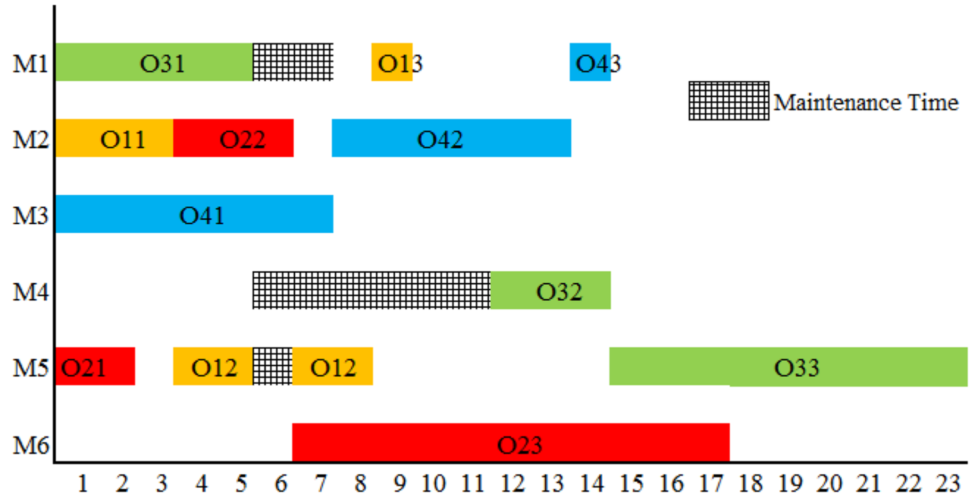
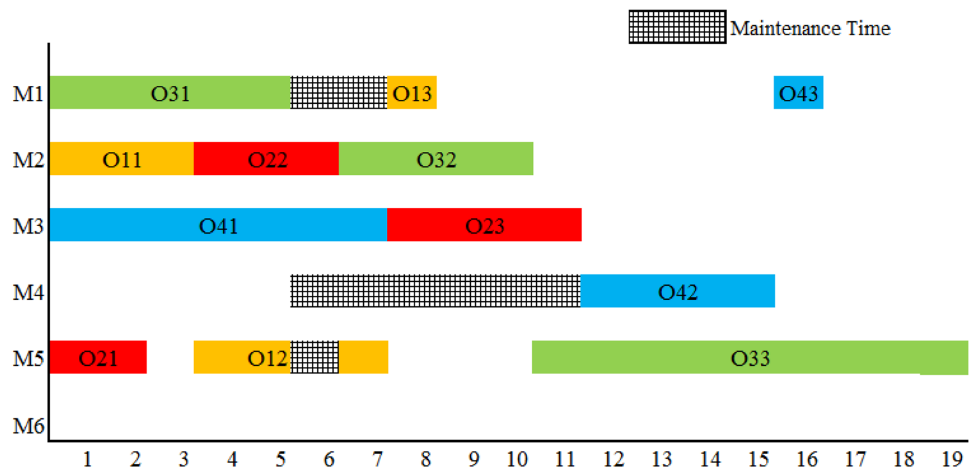


Fig. 13 Gantt chart for scheme a (scene 3) using the CPPS



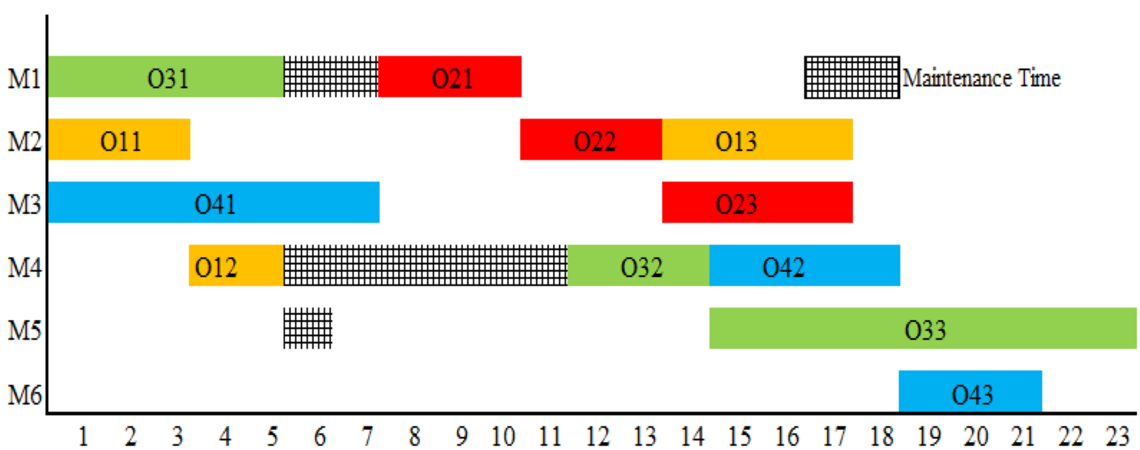


Fig. 14 Gantt chart for scheme b (scene 3) using the RS

components of PMDT are explored, especially five kinds of models (PDM, GSM, MAM, BRM and DFM) are illustrated as PMDT for CPPS towards smart shop-floor. (2) Based on PMDT, the architecture of digital twin-driven CPPS is designed as an industrial reference of digital twin. It includes five layers: application layer, model layer, data

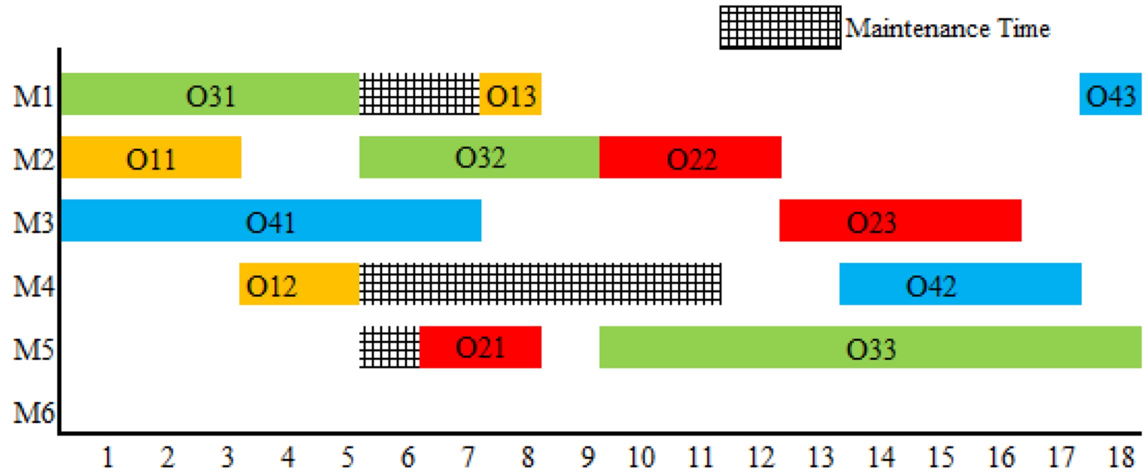


Fig. 15 Gantt chart for scheme b (scene 3) using the CPPS

Table 4 Results using the CPPS and the RS

Scene	Scheme	CPPS		RS	
		f1	f2	f1	f2
1	a	17	0	20	3
	b	17	0	17	0
2	a	17	0	18	1
	b	18	1	20	3
3	a	19	2	23	6
	b	18	1	23	6

layer, network layer, physical layer. (3) The blisk manufacturing is taken as an example to illustrate the application of digital twin-driven CPPS. Future work will focus on the following aspects: (1) how to improve these five models (PDM, GSM, MAM, BRM and DFM) more accurately. (2) The smart shop-floor simulation based on PMDT. (3) Smart interconnection and interaction between PMDT and physical shop-floor. (4) More production services and more application areas of CPPS.

Acknowledgements This paper is partially supported by National Natural Science Foundation of China (No. 51705472), Excellent Youth Foundation of Science and Technology Innovation of Henan Province (No. 184100510001), and Key Scientific Research Projects of Henan Higher Education (No. 18A460033, 18A460034). The authors are very much thankful to all reviewers for their constructive criticisms and suggestions that helped to improve this paper.

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