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Defining a Digital Twin-based Cyber-Physical Production System for autonomous manufacturing in smart shop floors

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Smart manufacturing is the core idea of the fourth industrial evolution. For a smart manufacturing shop floor, real-time monitoring, simulation and prediction of manufacturing operations are vital to improve the production efficiency and flexibility. In this paper, the Cyber-Physical System (CPS) and Digital Twin technologies are introduced to build the interconnection and interoperability of a physical shop floor and corresponding cybershop floor. A Digital Twin-based Cyber-Physical Production System (DT-CPPS) is further established, and the configuring mechanism, operating mechanism and real-time data-driven operations control of DT-CPPS are discussed in detail. It is expected that DT-CPPS will provide the basis for shop floors to march towards smart manufacturing.

Keywords: Smart manufacturing; Digital Twin; Cyber-Physical Production System (CPPS); autonomous manufacturing; operations control

1. Introduction

The production system has long been the core component of the manufacturing industry. Increasing product variants and individualised demands require more flexible and sustainable production systems (Chan et al. 2017, Ding and Jiang 2017a). Traditional production systems mainly suffer from low efficiency and clumsy responses due to non-transparency and feedback lag of the manufacturing operations. With the development of new generation information and communication technologies, the production mode has been shifting from mass production and to mass individualisation (Tao et al. 2017c), and the corresponding production system has been evolving from automated to autonomous. Smart manufacturing, as a concrete embodiment of mass individualisation, has been proposed in many national strategies such as Industry 4.0, Advanced Manufacturing Partnership Plan and Made in China 2025.

Cyber-Physical System (CPS) and Digital Twin technologies are the key enablers of smart manufacturing. The main idea of CPS is to build bi-directional interaction channels between the physical and cyber worlds, and establish an Internet of Things (IoT) in the physical world to connect various sensors, actuators and controllers with products and equipment for real-time data perception, transmission, processing, feedback and service (Liu et al. 2017). As the key technology of CPS, Digital Twin provides a clear and feasible way to realise the functions of CPS. It is a data and model-based system modelling method that emphasises the simulation synchronisation of the physical world and cyber world (Schleich et al. 2017). It builds a virtual twin of a physical entity (or system) to transparentise the geometrical/physical/behavioural status of the physical entity (or system) and provide the real-time simulation optimisation and control of the corresponding performance of the physical entity (or system).

In this situation, how to utilise the CPS and Digital Twin technologies to enhance the transparency in the production systems and facilitate the real-time production control has become a promising research topic. Although much literature has been devoted to CPS and DT-based production systems, such as IoT configuration for smart interconnection, shop floor modelling for transparency, manufacturing data integration for sharing and Big Data analysis for production control (Kumar et al. 2016, Zhong et al. 2017, Yin et al. 2018), there are still some limitations or disadvantages to be dealt with:

(1) Machine-oriented virtualisation and network access (including interfaces, protocols, digital models, etc.) has been configured, together with the machine operating data perception/transmission/processing methods. However, parts to be manufactured, as another important kind of participants in a production system, their connection to the

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industrial network has seldom been discussed. Besides, the self-X intelligence of parts and the autonomous interaction between parts and machines are seldom excavated. Thus the configuration of smart parts and smart resources (e.g. machines, industrial robots) should be carried out and they should be interconnected within the industrial network for information interaction and sharing.

(2) With the aid of Manufacturing Execution System (MES) and other information systems, traditional production systems can perceive the real-time production data and monitor the production statuses such as progress, quality and workload. However, the subsequent exception or error handling relies on manual efforts for supervision and reconfiguration, which is centralised and with low efficiency. Thus the mapping and simulation synchronisation between the physical and cyber production systems, together with the autonomous operations control methods should be carried out.

To solve these problems, we first define a Digital Twin-based Cyber-Physical Production System (DT-CPPS) and propose the framework reference model of DT-CPPS. Second, the configuring mechanism of DT-CPPS, including physical shop floor (PSF) configuration and cybershop floor (CSF) configuration, is discussed. In the PSF configuration, parts to be manufactured and the corresponding resources are endowed with smart capabilities of self-perception and autonomy, and they are interconnected through the industrial network. In the CSF configuration, the logical mapping and cyber-physical mapping of PSF and CSF will build a Digital Twin model of the physical production system, together with relevant data channels. The bi-directional interaction and interoperability between the PSF and CSF can simulate synchronously the actual statuses to support efficient production control, rapid disturbance response and flexible production configuration of smart factories (Nagadi et al. 2018, Wang et al. 2016a). Third, the operating mechanism of DT-CPPS is proposed for synchronisation and interoperability between PSF and CSF. Fourth, detailed function modules for autonomous operations control of DT-CPPS, including real-time manufacturing data processing, predictive machine sequencing and responsive production scheduling strategies, are discussed. These function modules are some of the enablers to realise autonomous manufacturing. By applying CPS and Digital Twin technologies into the production system, the comprehensive flow from digital shop floor modelling, manufacturing data perception/transmission/processing, to synchronised simulation and operations control of production system can be transparently managed and optimised.

On that basis, the contribution of this paper can be concluded as follows: (1) the PSF, CSF and DT-CPPS are systematically configured, which endow the parts to be manufactured and the corresponding resources with self-X intelligence, and model them as Digital Twin for smart interconnection and interaction; (2) the information interaction between PSF and CSF and the operating mechanism of DT-CPPS are established to facilitate autonomous manufacturing, in which smart parts collaborate with smart resources to produce themselves; (3) the real-time data-driven manufacturing operations control of DT-CPPS is explored, the manufacturing data process method, Digital Twin-based responsive production scheduling method and predictive machine sequencing method are built as exemplary function modules of DT-CPPS. The proposed DT-CPPS will provide a feasible solution to enhance the transparency in production systems and facilitate the data-centric and model-based simulation/operations control for the aim of autonomous manufacturing.

The rest of this paper is organised as follows: Section 2 summarises the related work of CPS/CPPS and autonomous manufacturing and Digital Twin technology. Section 3 clarifies the concepts and framework of DT-CPPS. The next two sections discuss the configuring and operating mechanisms of DT-CPPS, respectively. In Section 6, the real-time data-driven manufacturing operations control of DT-CPPS is researched. A demonstrative case is studied in Section 7 to verify the feasibility and practicality of the proposed DT-CPPS. Finally, discussion and conclusions are given.

2. Related work

2.1. CPS/CPPS and autonomous manufacturing

In order to respond quickly to unexpected events or disturbances without central re-planning, production systems for smart shop floors need to be more autonomous. As to autonomous manufacturing, machines and other resources should be smart, they need to know their capabilities and states both historically and currently (Rosen et al. 2015). Besides, they can perform their tasks with less detailed programming and human control. Meantime, parts should be smart and they need to know how they are manufactured and their current progress (Ding et al. 2017b). Through autonomous interactions among parts and resources, production decisions, resource orchestration and execution control can be made by them collaboratively (Park and Tran 2011). The autonomy of smart parts and resources enhances the flexibility and response speed of smart shop floors.

Agent, knowledge-based methods and autonomous discrete event simulation can be applied to realise production autonomy. Park and Tran (2012) presented an autonomous manufacturing system where work pieces, machines, robots and other resources are controlled by the corresponding cognitive agents. The system reacts to disturbances autonomously based on the reaction of each agent or on their cooperation. Žapčević and Butala (2013) proposed the concept of a self-learning autonomous manufacturing system that introduces a learning loop composed of data acquisition, data mining and knowledge-building models. Nonaka et al. (2015) proposed a closed-loop digital manufacturing system with an autonomous statistical analytics module and an autonomous discrete event simulation module to realise flexible production.

As the new information technologies develop, CPS/CPPS that connects the physical and cyber worlds to reach the goals of self-X (self-perception, self-learning, self-configuration, self-control, etc.), flexibility and autonomy is proposed. According to Lee et al. (2015), CPS/CPPS are highly interconnected, multi-layered, networked systems of hardware, software and a variety of physical entities, and a 5C architecture of CPS/CPPS is proposed. In some sense, CPS/CPPS can be viewed as an embodiment of autonomous manufacturing. Liu et al. (2015) discussed the horizontal integration and vertical integration of CPPS. Smart machines and other production facilities are endowed with the abilities of controlling each other independently, information exchange autonomously and triggering actions automatically. Ribeiro and Bjorkman (2017) compared the standard automation solutions with CPPS conceptually from four aspects: (1) module, its boundaries and actuation scope, (2) module's interfaces, (3) control strategy and path, and (4) supporting technologies. The results show the superiority of CPPS in improving the reconfigurability and flexibility of manufacturing systems. Francalanza et al. (2017) proposed a knowledge-based tool (i.e. prototype digital factory tool) for designing CPPS to effectively deal with the complexity and time-consuming efforts in the manual design method. Tomiyama and Moyen (2018) researched the resilient architecture of a CPPS to deal with the disturbances and failures autonomously in a discrete event process. Rojas et al. (2017) proposed a conceptual framework to enable network connectivity of CPPS, in which the end nodes of a smart factory are homogenised and integrated through centralised backbone network. Vrabic et al. (2018) discussed an agent-based approach to distributed control in CPPS and defined the agents are rationally bounded and can only interact with a part of the whole system. Liu et al. (2017) introduced a new paradigm called Cyber-Physical Manufacturing Cloud (CPMC) to bridge gaps among cloud computing, CPS and manufacturing. To deal with the scalability requirements of a smart factory, Weyer et al. (2016) discussed the modelling and simulation framework and methods of CPPS, and an example from the automotive industry is studied to verify the feasibility.

From the literature above, we can conclude that autonomous manufacturing is a key point for a smart shop floor. The implementation of CPS/CPPS makes it possible to achieve autonomous manufacturing by connecting PSF and CSF. However, the autonomy of smart parts and resources will improve the complexity and uncertainty of production system's behaviour. Therefore, model-based simulation methods, such as Digital Twin, are urgently needed to simulate and optimise manufacturing operations (i.e. actions of smart parts and resources) of the whole lifecycle.

2.2. Digital Twin technology

Digital Twin technology was first proposed by Grieves in 2003 and then applied in NASA's Apollo project (Tao and Zhang 2017a). The NASA integrated technology roadmap defined the Digital Twin as 'an integrated multi-physics, multi-scale 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' (Glaessgen and Stargel 2012). The integration of the physical entity and virtual entity allows context-specific decisions during the entity's lifecycle. It is mentioned that Digital Twin represents the prerequisite for the development of CPS/CPPS and provides a clear way to realise the main idea of CPS/CPPS. When applied in the manufacturing industry, in some sense it can be interpreted from two aspects: (1) product realisation standpoint and (2) production system standpoint.

From the product realisation standpoint, Digital Twin model of a product is built by mirroring the physical product into the virtual one. With the product Digital Twin, the gap among all stages of product realisation, from conceptual design to handover (even to use and service), can be bridged for shortening the time to market and increasing the product development performance (Rosen et al. 2015). Schleich et al. (2017) focussed on shaping the Digital Twin for the product design and production process, and proposed a reference model of product Digital Twin to realise geometrical variations management. Söderberg et al. (2017) also discussed Digital Twin-based real-time geometry assurance for individualised product production. Abramovici et al. (2017) researched the reconfiguration of smart products during their use phase across different engineering domains. The reconfiguration is enabled by virtual product twins that contain models and data of all virtual and physical product instances along the entire product lifecycle.

From the production system standpoint, Digital Twin technology is utilised to design the shop floor layout, production line and process flow for individualised demands, and to manage the production operations in shop floor. Zhang et al. (2017) discussed a Digital Twin-based approach to design and decouple a hollow glass production line. The newly designed production line was tailored for individualised designing demand and bridged the gap between physical and digital manufacturing systems. Stark et al. (2017) proposed a Digital Twin-based architecture design approach for the modularised design of CPPS as well as the corresponding system validation and verification methods. Tao and Zhang (2017a) and Tao et al. (2017b) proposed the concept of Digital Twin Shop floor (DTS) to converge the manufacturing physical world and the virtual world. They pointed out four key components of DTS: physical shop floor, virtual shop floor, shop floor service system and shop floor Digital Twin data. Alam and Saddik (2017) presented a Digital Twin architecture reference model for the cloud-based CPS (C2PS) and analytically described its key properties of computation, control and communication.

From the literature above, it can be concluded that many research studies were devoted to Digital Twin technology from both the aspects of product realisation and production system operations. However, they seldom combine the product Digital Twin with the shop floor Digital Twin. Besides, it lacks the conceptual basis for implementing Digital Twin-based monitoring, simulation, prediction and feedback control of manufacturing operations in smart shop floors, such as real-time state monitoring and synchronisation, disturbance-responsive production scheduling strategy and autonomous resource sequencing/orchestration.

3. Clarification of DT-CPPS

3.1. Definitions

A production system is a collection of integrated equipment and human resources, whose function is to perform value-added production operations on a starting raw material, part or set of parts (Groover 2016). In smart manufacturing, the production system should be open, stochastic, self-X and autonomously operated. Driven by CPS and Digital Twin, it has been evolving into a DT-CPPS. To better understand DT-CPPS, some related terms are clarified.

Definition 1: Smart objects are defined as the physical entities in DT-CPPS that are endowed with the intelligence of self-X and autonomy, such as smart parts, smart resources (machines, tools, vehicles, etc.). They are equipped with radio frequency identification (RFID) devices, sensors and embedded system devices to realise automatic identification, state data perception, intelligent interactions and autonomous decision-making (Ding and Jiang 2017a). Especially, smart parts are the handovers of PSF that will go through the raw materials to the work-in-progress and to the final finished parts.

Definition 2: DT-CPPS is a kind of PSF/CSF-integrated production system that transforms raw materials into finished parts or products by autonomous interaction and coordination among smart objects in both the physical world and the cyber world. The physical embodiment of DT-CPPS is a smart shop floor (i.e. PSF) and the virtual embodiment is a Digital Twin of the shop floor (i.e. CSF). Note that CSF has the same initial layout, tasks, resources, process plans and manufacturing operations as PSF. Through real-time mapping and interoperability of PSF and CSF, manufacturing operations can be transparently monitored and dynamically managed, and the flexibility and controllability of PSF can be enhanced.

Definition 3: Digital Twinning is a process of building a Digital Twin in the cyber world of the physical objects and systems, and establishing data channels for cyber-physical interconnection and synchronisation. Each physical object and system has a Digital Twin, e.g. part Digital Twin, machine Digital Twin, shop floor Digital Twin. The combination of physical objects and corresponding Digital Twins generates various CPPS nodes and all the nodes in the shop floor make up the final CPPS.

3.2. Systematic framework

Based on the above definitions, the framework of DT-CPPS can be described as in Figure 1. The input of DT-CPPS includes orders, customer requirements and raw materials. With the rapid development of global markets, the inputs are becoming

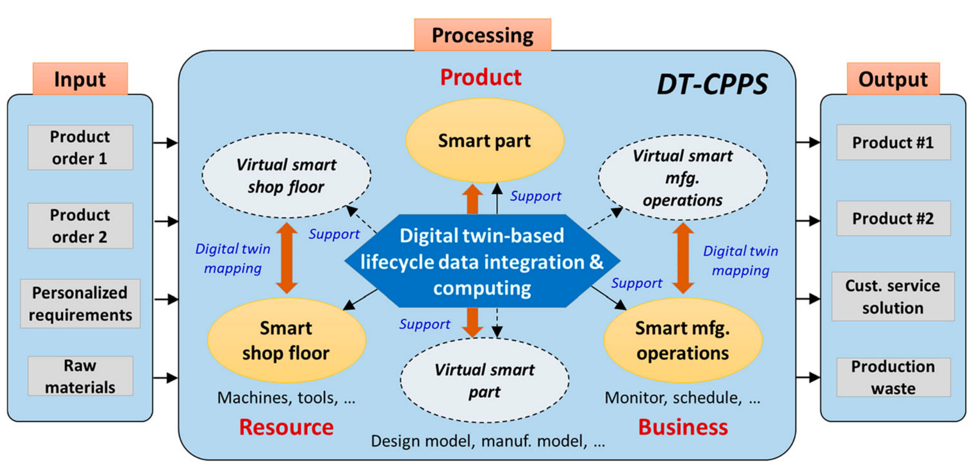

Figure 1. Framework of DT-CPPS.

more and more individualised and dynamic. The processing of DT-CPPS relies on two conditions: (1) the cohesion of three physical portions (i.e. smart part, smart shop floor and smart manufacturing operations); (2) the mapping and interaction of physical portions with virtual portions (i.e. virtual smart part, virtual smart shop floor and virtual smart manufacturing operations). These portions are supported by the Digital Twin-based lifecycle data integration and computation technologies and tools in DT-CPPS. During production, these six portions will function around the technological support in an autonomous way. A social network in CSF can be abstracted from the interactions of physical objects and even humans. Analysis of this social network can help to discover the hidden relations and rules among them. Finally, the output of DT-CPPS is the finished parts/products, customer service solutions and production wastes.

4. Configuring mechanism of DT-CPPS

After clarifying the definitions and framework of DT-CPPS, the configuring mechanism of DT-CPPS is further discussed, which includes PSF configuration and CSF configuration.

4.1. PSF configuration

4.1.1. Smart parts configuration

The parts to be manufactured are endowed with intelligence so as to know the sequence of manufacturing operations, including which kind of machine is needed to perform a certain operation and how is the production progressing. Based on that, parts will interact proactively with other physical objects in PSF to make decisions through the beginning (raw materials) to the end (handovers). To achieve this, an RFID tag, an embedded system device and a travelling pallet are configured to each part or each batch of parts (Ding and Jiang 2017a), as shown in Figure 2(a). The RFID tag has a unique code for automatic identification and data perception. It stores for reference the part's manufacturing operations and other useful information. An embedded system device (e.g. Raspberry Pi, BeagleBone Black) integrated with various software application tools undertakes the manufacturing data computing, storing and transmission. It is the embodiment of a part's intelligence. The travelling pallet is used for easy loading and unloading of parts. These smart parts contain all the information and data of their lifecycle and form a huge distributed data storage. After listing the symbols in Table 1, the part configuration scheme is formalised as

$$SP_i = \{PT_{id}, O_{id}, OInfo, PSet, Cp, Cl, PLog\}, \tag{1}$$

$$PSet = \{P_{i,1}, \ldots, P_{i,j}, \ldots, P_{i,n}\} \bowtie \mathbf{R}^n, \ \forall j \in [1, n], \tag{2}$$

$$P_{i,j} = \{P_{type}, Qr, St, Dt, Info\}. \tag{3}$$

4.1.2. Smart resources configuration

The manufacturing resources in PSF (e.g. machines, vehicles, assisting tools) also need to be smart. Nowadays, sensors, actuators and embedded system devices have become more affordable and available, thus it is feasible to deploy them on the physical resources to achieve smart capabilities, as shown in Figure 2(b).

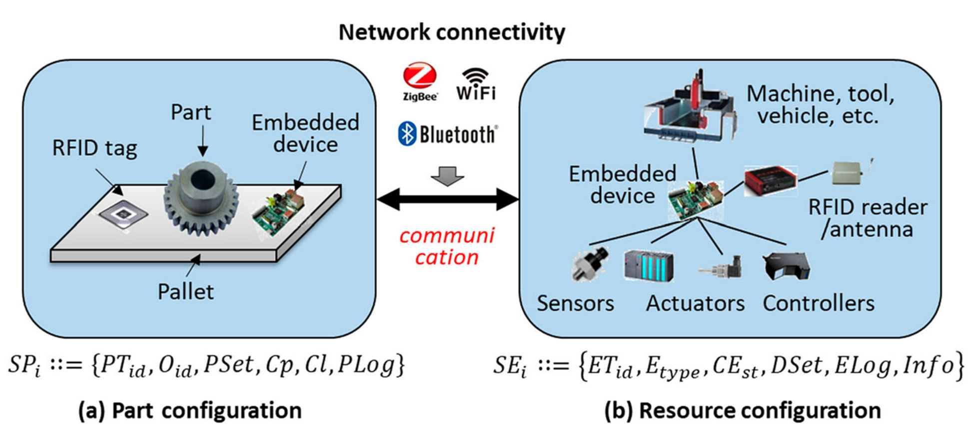

Figure 2. PSF configuration.

Table 1. List of symbols.

Symbol	Meaning	Symbol	Meaning
PT_{id}	unique code of smart part SP	$\mathbf{R}^n$	matrix of the machine list, tool list and operator list of manufacturing operations
O_{id}	order number	$P_{i,j}$	jth manufacturing operation of SP_i
$OInfo$	detailed information (priority, amount, batches, etc.) of O_{id}	P_{type}	type of $P_{i,j}$ such as turning, milling and transporting
$PSet$	planned manufacturing operations set	Qr	quality requirements of $P_{i,j}$
Cp, Cl	current operation and current location of SP	St, Dt	start time and the processing time of $P_{i,j}$
$PLog$	execution logs of manufacturing operations	$Info$	other detailed information of $P_{i,j}$

By attaching various sensors, each resource can perceive its own running status and environment. The embedded system device has the embedded data computing and communication capabilities and acts as an agent to gather real-time data from sensors via HTTP requests, parse these data into engineered information via Python applications and communicate with others using wired or wireless communications via data exchange protocols (e.g. TCP/IP, RTP) with data format of XML or JSON. Since RFID technology has been widely applied in manufacturing (Zhong et al. 2013, Ding et al. 2018), an RFID reader/antenna is deployed to automatically identify the RFID-tagged parts entering its radiation range. Therefore, smart resources can judge whether the incoming part will be processed by it, and what operations should be performed on the smart part. On that basis, smart resources and smart parts can autonomously interact with each other and make collaborative decisions via a dialog mechanism. The resource configuration scheme is formalised as

$$SE_i = \{ET_{id}, E_{type}, CE_{st}, DSet, ELog, Info\}, \tag{4}$$

$$DSet = \{N, E, S, V, D\}, \tag{5}$$

where ET_{id} is the unique code of the smart resource SE_i; E_{type} classifies the resource type into machine, tool, vehicle, etc.; CE_{st} represents current state of SE_i including idle, occupied and breakdown; $DSet$ stands for the set of sensor data that indicates the working state of SE_i, including noise N, energy consumption E, speed S, vibration V, displacement D and so on; $ELog$ records the logs when SE_i operates; $Info$ stores the detailed information of SE_i such as model, key parameters, operator in charge, lifetime, etc.

Considering there are complicated relationships among these smart resources, e.g. a milling machine needs milling cutters and clamps to accomplish a milling process, the relational matrix of smart resources is defined as follows to clarify the resource composition rules:

$$R_{SE} = [R_{i,j}]_{N\times N}, \forall i, j, R_{i,j} \in \{0, 1, 2\}, \tag{6}$$

where R_{SE} is the relational matrix of smart resources, its element $R_{i,j}$ represents the relationship between ith and jth resources, and their relationship types include 'irrelevance', 'dependence' and 'dominance', which are noted by 0, 1 and 2, respectively.

On that basis, semantic ontology is used to model the smart parts and smart resources, describing their static and dynamic attributes, together with their relationships.

4.1.3. Network connectivity configuration

Network connectivity is guaranteed by deploying network facilities in PSF. Location-fixed smart resources such as machines can access the Internet via cable network. While smart parts and moving resources such as vehicles connect to the wireless network (e.g. ZigBee, Wifi, Bluetooth), which are cost-effective and easy-to-use ways for anytime and anywhere network access. All of them form a shop floor-level IoT. Further, two kinds of databases – private database and public database – are configured separately to store hierarchically the manufacturing data and information. The private database is location independent and remotely accessible, and it is deployed on each embedded system device, while the public database is deployed on the cloud. The private database stores the real-time data and the pre-processed information, while the public database stores order information, production rules, historical knowledge and other engineered information. Meantime, pre-processed information from the distributed private databases is further synchronised to the public database. The combination of private database and public database indicates the trend of the cloud-based distributed data storage and computing (Ding et al. 2018). Besides, the protocols for smart object access such as MTConnect (Liu et al. 2016), AutomationML (Schroeder et al. 2016) and OPC UA need to be configured.

After the smart parts, smart resources and industrial network are configured, PSF can be finally formalised as

$$PSF = \mathbf{SP} \bowtie \mathbf{SE}, \tag{7}$$

where **SP** is the set of smart parts manufactured in PSF; **SE** is the set of smart resources; $\bowtie$ denotes **SP** and **SE** are logically connected in shop floor's cable or wireless network. Note that **SP** and **SE** are both dynamic, the coming or finished orders will update **SP**, and the newly inserted smart resources will update **SE**.

4.2. CSF configuration

After PSF is configured, another task is to configure CSF, as described in Figure 3. CSF configuration includes logical mapping (build a Digital Twin model of PSF) and cyber-physical mapping (build data channels for PSF–CSF interoperability). CSF configuration greatly relies on the utilisation of various modelling tools and data computing algorithms.

4.2.1. Logical mapping

As the methods to build the Digital Twin of a part have been widely researched, this paper focusses on the Digital Twin modelling of shop floor. Modelling tools such as Plant Simulation®, Demo 3D® and others are available. Reference models with templates of static attributes, motion script, control scheme and communication interface (Zhang et al. 2017) are adopted to initialise a Digital Twin model of PSF, i.e. CSF. This model not only contains the physical layout and 3D geometry information but also contains the dynamic engineered information of each physical object. Some of this information is inherited from the physical object's inherent attributes and parameters, while some is dynamically synchronised from PSF. Afterwards, the 'element-behaviour-rule' multi-dimensional modelling of smart shop floor is established to simulate the real-time operating performance, such as process planning simulation, production scheduling simulation and exception/error simulation.

Based on that, logical mapping between PSF and CSF is achieved. The shop floor Digital Twin modelling and simulation is important to improve the operation efficiency and flexibility and reduce extra cost. The Digital Twin model (i.e. CSF) is formalised as

$$CSF = \mathbf{SP}' \bowtie \mathbf{SE}', \tag{8}$$

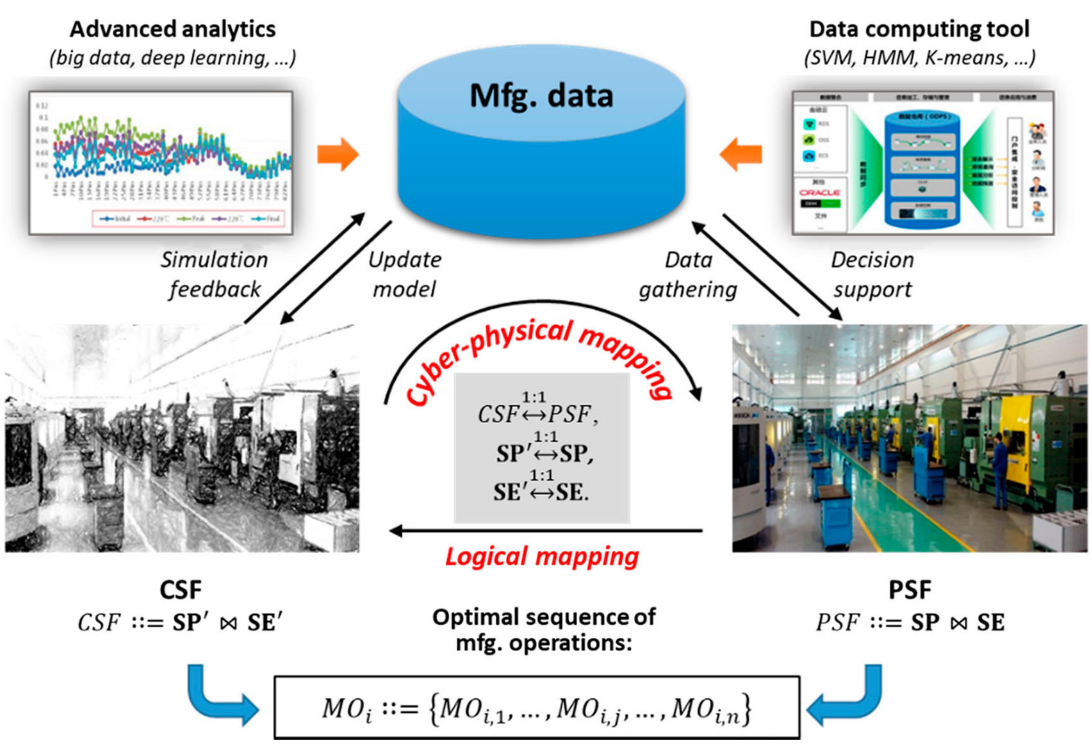

Figure 3. CSF configuration.

where $\mathbf{SP}'$ and $\mathbf{SE}'$ stand for the Digital Twins of smart part **SP** and smart resource **SE** respectively, which own the same elements and attributes as **SP** and **SE**.

4.2.2. Cyber-physical mapping

After building the shop floor Digital Twin model, the channels for interoperability between PSF and CSF should be established from the data-driven perspective. Data interfaces and protocols, e.g. MTConnect, AutomationML, XML, TCP/IP and HTTP, are used to realise the cyber-physical model mapping and data synchronisation between PSF and CSF. The data/information from PSF and CSF is bi-directionally exchanged via standard data exchange format.

The cyber-physical mapping of PSF and CSF together with their elements are formalised as

$$CSF \overset{1:1}{\leftrightarrow} PSF, \mathbf{SP}' \overset{1:1}{\leftrightarrow} \mathbf{SP}, \mathbf{SE}' \overset{1:1}{\leftrightarrow} \mathbf{SE}, \tag{9}$$

where operator $\leftrightarrow$ represents the one-to-one mapping relationship between pairs of objects in the cyber and physical worlds respectively.

Enabled by the increased computing capabilities of CSF and various data service applications such as Support Vector Machine (SVM), Hidden Markov Model (HMM), K-means Clustering and Deep Neural Network (DNN), heterogeneous real-time manufacturing data from PSF can be analysed immediately in CSF. Thus CSF duplicates the historical manufacturing operations in PSF and optimises the next operation iteratively by simulation. The decisions made through CSF simulation will be transferred to PSF and parsed by smart parts and resources. Through PSF–CSF simulation and interoperability, an optimal sequence of manufacturing operations can be achieved, which will be dynamically adjusted according to the real-time situations of PSF.

$$MO_i = \{MO_{i,1}, \ldots, MO_{i,j}, \ldots, MO_{i,n}\}, \tag{10}$$

where MO_i is the optimal set of manufacturing operations, it is the actual reorganisation of the previous *PSet*; $MO_{i,j}$ is the actual *j*th manufacturing operations of MO_i, which may be identical to the planned $P_{i,j}$ or not.

5. Operating mechanism of DT-CPPS

5.1. Information interaction within and between PSF and CSF

On the basis of PSF/CSF configuration, the information interaction can be classified into two aspects: (1) within PSF and (2) between PSF and CSF.

On one hand, within the PSF, smart parts will communicate with smart resources during production in a broadcast way or a peer-to-peer way to decide optimal production sequences dynamically and react to disturbances collaboratively. The communication protocols could be DDS, MQTT and HTTP. A multi-role negotiation mechanism (Wang et al. 2016a) that clarifies the request-response and announce-bid actions can be used. With the broadcast way, smart parts will announce its next operation or process to all the smart resources, and smart resources bid for it according to their real-time capabilities and the Digital Twin simulation results. With the peer-to-peer way, one smart object whether it is a smart part or smart resource will publish a request for relevant data or information to the other certain smart object, when the latter smart object receives this message, it will gather the certain data or information in time and feed back to the former smart object for response.

On the other hand, the information interaction between PSF and CSF is realised by cyber-physical mapping in Section 4.2.2. The multi-modal data from PSF are uploaded to CSF via data interfaces in a request–response mechanism, to realise near real-time shop floor transparency and production simulation. Meanwhile, the results of simulation optimisation are parsed into control commands or information and further transmitted to each smart object.

5.2. Operating flow for autonomous manufacturing

The operating flow of DT-CPPS is illustrated in Figure 4, which is accompanied with the part manufacturing lifecycle starting from order receiving alongside to finished part delivering. It strengthens the interoperability of PSF and CSF and the real-time data-driven decision-making, which improves the flexibility, controllability and efficiency of shop floor manufacturing. It can be seen from Figure 4 that there are four main modules: Digital Twin simulation, real-time data processing, manufacturing operations execution and responsive production decision-making.

First, when an order is received by DT-CPPS, detailed information of the part type, manufacturing requirements, quantity, quality and cost is written in an RFID tag attached to the part or the batch of parts. The manufacturing operations for

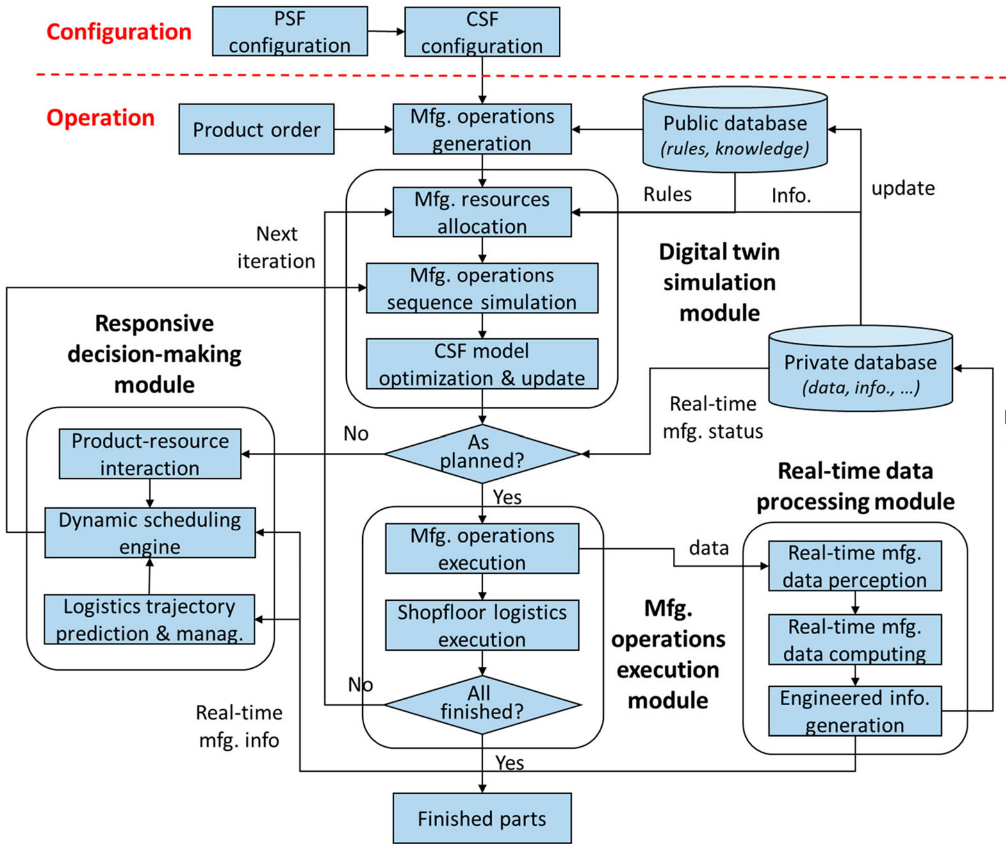

Figure 4. Operating flow of DT-CPPS.

each part feature are generated based on the above information and the operation decomposition rules stored in the public database.

Second, manufacturing resources allocation and machine sequencing are simulated by the Digital Twin model. The simulation is performed in a near real-time manner based on the information derived from on-site private databases and the knowledge stored in the public database. Following the time sequence, the resource allocation and relevant planning of each manufacturing operation will be simulated. Various data computation and analysis tools are used to facilitate the simulation. Based on the simulation results, CSF Digital Twin model will be dynamically optimised and updated. It notifies PSF about the computation findings and sends commands to make changes or reconfigure system parameters if required.

Third, if the statuses of current manufacturing operation match with the simulation results, the next simulation-proved optimal manufacturing operation will be executed, together with the shop floor logistics. If not, the smart part will communicate with smart resources to respond to the current statuses, and the dynamic scheduling engine will be invoked to find available solutions for the next operation. This scheduling engine works by inputting real-time manufacturing information, applying intelligent algorithms (e.g. Artificial Neural Network – ANN, Ant Colony Optimisation – ACO) for processing and outputting an optimal scheduling strategy. Then the scheduling strategy will be synchronised to CSF for follow-up simulation.

Finally, when all the manufacturing operations are finished, a smart part is generated for delivery.

It should be noted that both the Digital Twin simulation module and the responsive decision-making module highly rely on the real-time data processing module. The next section discusses some key functions of the above modules in detail.

6. Real-time data-driven operations control of DT-CPPS

6.1. Manufacturing data processing

The Digital Twin model is not just a collection of all the digital objects but is also a collection of all lifecycle-related, structured and connected information/semantics. For DT-CPPS, heterogeneous manufacturing data (e.g. process data, RFID data, sensor data, etc.) are gathered, whether in an event-driven acquisition way or continuous acquisition way. The configured

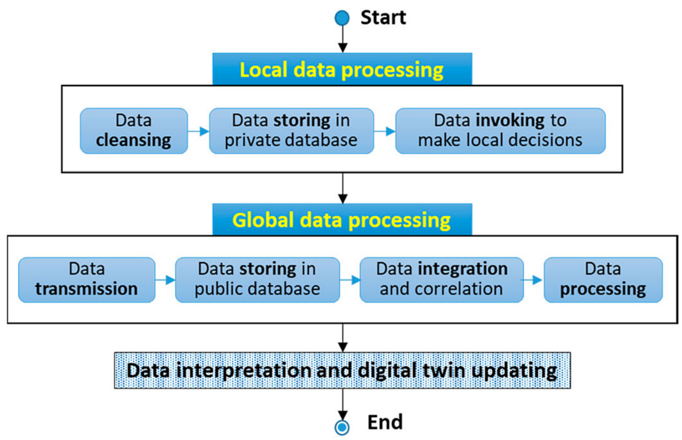

Figure 5. Distributed manufacturing data processing.

sensors, RFID devices and embedded system devices are responsible for real-time data perception and logging. Big data analytics is an efficient way to excavate hidden values and correlations from the heterogeneous, sparse, large-volume manufacturing data, which supports the realisation of self-organised production system (Wang et al. 2016b). Considering the data are stored hierarchically in private databases and public databases, a distributed manufacturing data processing method should be utilised. This method includes two phases, i.e. local data processing and global data processing, as shown in Figure 5. The difference between local and global data processing is that the former is executed only for simple feedback and control of the distributed smart resources themselves, while the latter is executed for shop floor-level management and control. After these two phases, the data interpretation and Digital Twin updating should be finally dealt with.

6.1.1. Local data processing

For local processing, the real-time data perceived from different smart resources is first cleaned to eliminate the incomplete, inaccurate and duplicated data. The Sorted Neighbourhood Method (SNM) and K-means clustering algorithms compiled in form of Python applications are installed on demand in distributed embedded system devices to realise data cleansing. Then, the cleaned data is stored in the private database, and the Python applications in embedded system devices will invoke it to make real-time decisions and execute feedback control, e.g. issue a warning alert or stop a sensor working.

6.1.2. Global data processing

For global processing, the cleaned distributed real-time data is first uploaded through the shop floor network to the public database for backup. Then, the data is integrated according to a data correlation model. Afterwards, the data are processed using various algorithm-embedded application tools to excavate decision-assisted information and knowledge. Finally, the achieved information and knowledge are applied as rules or constraints for production decision-making, such as scheduling, exception monitoring and shop floor logistics optimisation.

6.1.2.1. Data correlation Considering the distributed manufacturing data are always associated with each other in a common shop floor environment, data correlation principles and rules should be established to better parse the cleaned data into meaningful engineered information. The manufacturing operations flow and time sequence can be viewed as the data correlation mainline. This means that each manufacturing data is attached to a certain manufacturing operation at a certain time point, thus a dynamic manufacturing data tree is generated which grows bigger as the manufacturing operations march ahead, as shown in Figure 6. It unveils dependencies between parts, resources, processes and operational characteristics that used to be hidden. In the data tree model, there is a data trunk ($\mathbf{DT}_i$) and different levels of data branches ($\mathbf{DB}_{i,j}$). $\mathbf{DT}_i$ corresponds to the manufacturing operations sequence as follows:

$$\mathbf{DT}_i \overset{1:1}{\leftrightarrow} MO_i, \tag{11}$$

where $\mathbf{DB}_{i,j}$ indicates different levels of correlated data set. Each branch integrates at least one sub-branch ($\mathbf{DB}_{i,j,z}$) or one data node ($DN_{i,j}^k$). Each data node is assigned a certain value or value set that is derived from the cleaned manufacturing data, such as smart resource-related data ($SE.DSet$), order-related data ($SP_i.OInfo$) and smart part-related data ($SP_i.PSet$).

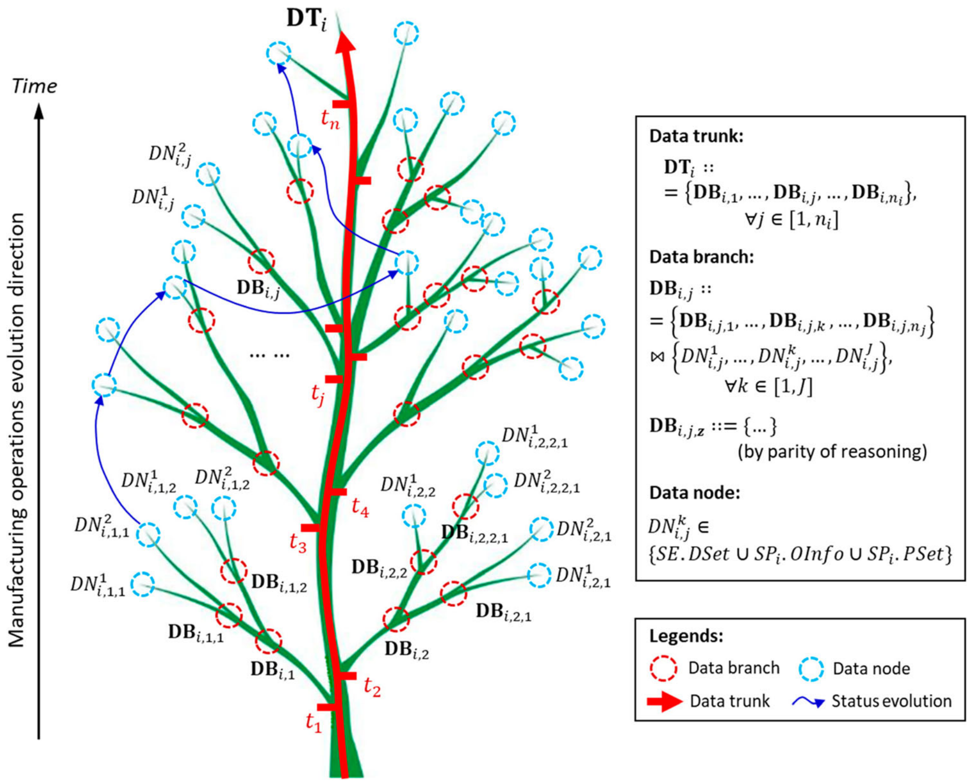

Figure 6. Manufacturing data model.

The relationships among data trunk, data branch and data node are illustrated in Figure 6 and formalised in Equations (12)–(14).

$$\mathbf{DT}_i = \{\mathbf{DB}_{i,1}, \ldots, \mathbf{DB}_{i,j}, \ldots, \mathbf{DB}_{i,n_i}\}, \forall j \in [1, n_i], \tag{12}$$

$$\mathbf{DB}_{i,j} = \{\mathbf{DB}_{i,j,1}, \ldots, \mathbf{DB}_{i,j,k}, \ldots, \mathbf{DB}_{i,j,n_j}\} \bowtie \{DN^1_{i,j}, \ldots, DN^k_{i,j}, \ldots, DN^J_{i,j}\}, \forall k \in [1, J], \tag{13}$$

$$DN^k_{i,j} \in \{SE.DSet \cup^S P_i.OInfo \cup^S P_i.PSet\}. \tag{14}$$

Take the turning process of a shaft on a CNC machine tool for example. Assume the shaft order is the second task of the smart shop floor and the turning process is the third process of shaft manufacturing. Thus heterogeneous real-time data from this turning process is integrated in $\mathbf{DB}_{2,3}$, which includes two data nodes (i.e. ambient temperature $DN^1_{2,3} = 28.5°\text{C}$ and humidity $DN^2_{2,3} = 35\%RH$) and two data sub-branches (i.e. CNC machine tool's status data set $\mathbf{DB}_{2,3,1}$ that includes mean values of spindle speed $DN^1_{2,3,1} = 602\,\text{rpm}$, spindle vibration $DN^2_{2,3,1} = 12\,\mu\text{m}$, noise $DN^3_{2,3,1} = 54\,\text{db}$ and so on; shaft's status data set $\mathbf{DB}_{2,3,1}$ that includes external surface roughness $DN^1_{2,3,2} = 12.6\,\text{Ra}$, outer circle diameter $DN^2_{2,3,2} = 62.7\,\text{mm}$, cylindricity $DN^3_{2,3,2} = 0.01\,\text{mm}$ and so on). Thus $\boldsymbol{DB}_{2,3}$ can be described as $\mathbf{DB}_{2,3} = \{\mathbf{DB}_{2,3,1}, \mathbf{DB}_{2,3,2}\} \bowtie \{DN^1_{2,3}, DN^2_{2,3}\}$.

Apart from this, during the turning process, the unique ID of the shaft and CNC machine tool can be used to index more data according to the mapping relationship in Equations (6) and (10). By connecting all the data branches/sub-branches in a time sequence, the real-time manufacturing data can be integrated horizontally and vertically as a data trunk, as shown by the red arrow line in Figure 6. Meantime, by integrating the attribute value at different time points of a common physical object, the status evolution process of this object can be revealed, which is essential for judging whether it is under proper operation status, as illustrated by the blue lines in Figure 6. In this situation, the manufacturing data model can also be viewed as a complex network where many network nodes (data branches or data nodes) are connected with each other with different strengths, and this network has the typical characteristics of the small world, self-organisation and self-similarity, and further, it evolves dynamically.

6.1.2.2. Data processing Based on the above data model, the next step is to excavate valuable information from the heterogeneous manufacturing data to support the shop floor's production control and decision-making. Different methods and algorithms are compiled as separate applications using Python language. In these apps, all the input and output data are standardised in XML format for easy transfer.

Classification algorithms such as decision tree, K-means clustering and SVM are used to cluster related data and calculate the accumulative effects of DT-CPPS operation, including machine status evaluation and worker workload balancing. For example, by classifying the machine tool's operation time for a specific kind of manufacturing processes, the average efficiency and workload of the machine tool can be achieved, which will provide suggestions to future process planning. DNN, random forest and HMM are used to predict manufacturing operations according to historical manufacturing data, including machine sequencing prediction and logistics trajectory prediction.

It should be noted that the real-time manufacturing data processing module is integrated in the CSF Digital Twin, and it supports the simulation analysis of CSF. The next section introduces the data processing-based functional simulation.

6.2. Digital Twin updating and simulation analysis

The data processing results should be interpreted and visualised in CSF to update the parameterised Digital Twin model and provide data support for synchronous simulation. The content of Digital Twin updating includes parts information, resources information and manufacturing operations information. The newly updated CSF will be re-evaluated to perceive the current operating status of the corresponding PSF. Based on that, simulations will be performed synchronously to predict the possible situations in PSF and provide available solutions. Two functional modules of Digital Twin simulation analysis will be discussed further, including HMM-based predictive machine sequencing and simulation-driven responsive production scheduling strategies. Through the iterative interaction and interoperability with CSF, PSF can achieve the goal of high flexibility, high efficiency and low cost.

6.2.1. HMM-based predictive machine sequencing

The machine sequencing problem can be viewed as the extension of responsive scheduling strategies. It is a kind of autonomous predictive scheduling strategy. The goal of machine sequencing is to find an optimal machine sequence for a certain process flow. As in the responsive scheduling strategies above, the current statuses of parts and resources are accessible with the aid of the disturbance recognition module. It can be seen that the next process of smart parts only relies on the execution result of the former process. Thus the simulation app integrating a HMM can be utilised to build the machine sequencing model.

As shown in Figure 7, suppose there are five machines with various capabilities in DT-CPPS. The process flow of a smart part (PF1–PF5) is given, and all the process features will be performed by the above machines. According to the initial process plan, a smart part enters the shop floor and searches for a proper machine for the first process. After the first process is finished, it will select a proper vehicle to deliver itself to another machine for the next process until all the processes are finished. During that time, the CSF Digital Twin will simulate the process execution status dynamically and predict the following process-machine pairs based on HMM. Here, HMM applies the historical experience to determine a machine sequence with max probability of occurrence. The predicted machine sequence will provide suggestions for selecting optimal machines for the actual processes. The red dashed lines in Figure 7 indicate the probable state transition of a smart part from one machine to another machine, and the black arrow lines indicate the optimal machine sequence with maximum probability.

On that basis, the machine sequencing problem can be viewed as a kind of HMM with known state transition probability, emission probability and observable state chain, and unknown hidden state chain. Here, the observable states mean different kinds of processes and the observable state chain is the process flow of a smart part, while the hidden state mean different kinds of machines and the hidden state chain is the machine sequence corresponding to the process flow. Thus HMM-based machine sequencing model can be formalised as

$$\lambda = (A, B, \pi), \tag{15}$$

$$Q = \{q_1, q_2, \ldots, q_N\}, V = \{v_1, v_2, \ldots, v_M\}, \tag{16}$$

$$I = \{i_1, i_2, \ldots, i_t\}, O = \{o_1, o_2, \ldots, o_t\}, \tag{17}$$

$$A = [a_{ij}]_{N\times N}, a_{ij} = p(i_{t+1} = q_j | i_t = q_i), \tag{18}$$

$$B = [b_{ik}]_{N\times M}, b_{ik} = p(o_t = v_k | i_t = q_i), \tag{19}$$

where λ describes the HMM model, A and B stand for the known state transition probability and emission probability, π is the initial probability. Equation (16) describes the set of possible hidden states and the set of possible observable states.

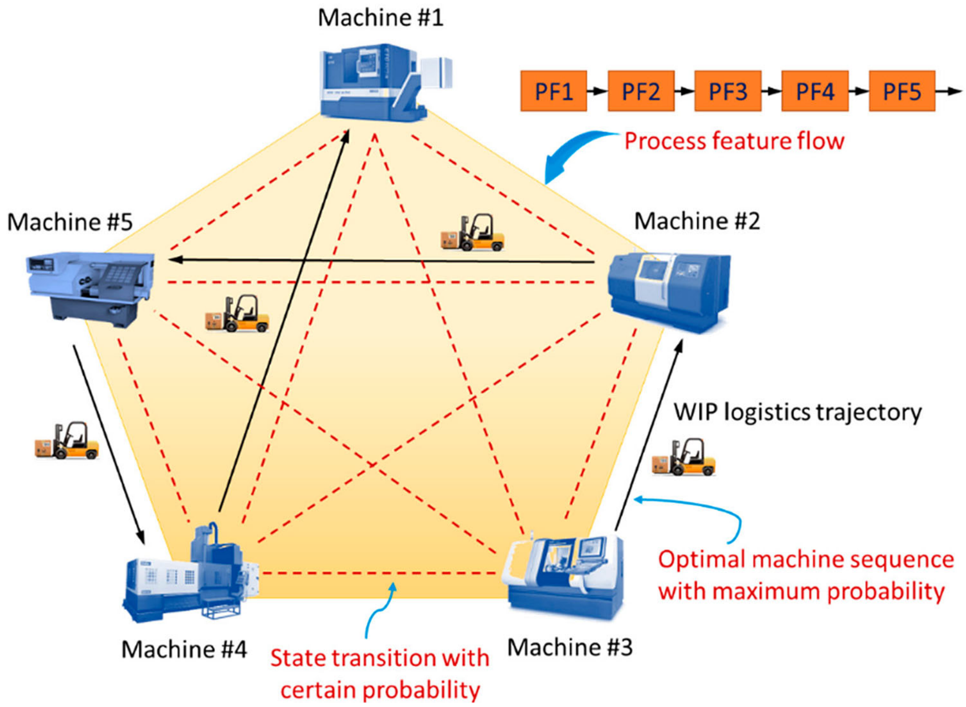

Figure 7. HMM-based machine sequencing mechanism.

Equation (17) describes the hidden state chain and the observable state chain. Equation (18) describes the calculation of the element of A, where i_t represents the hidden state at time t. Equation (19) describes the calculation of the element of B, where o_t represents the observable state at time t. On that basis, the observable state o_{t+1} with max probability $P(I|O)$ can be predicted.

Note that HMM is first learned from the historical manufacturing data and then applied to predict the machine sequence. Not only can it predict the optimal machine sequence but also can predict the shop floor logistics trajectory because each state transition of a smart part from one machine to another machine indicates a logistics trajectory. Based on the logistics trajectory, the shop floor layout can be further optimised to improve production efficiency and cut down production cost.

6.2.2. *Simulation-driven responsive production scheduling strategies*

As a dynamic system, DT-CPPS always encounters various disturbances. These disturbances can be dominant or recessive, and they can be excavated from the real-time manufacturing data. Traditional methods seldom discuss the responsive production scheduling strategies for real-time disturbance responses because there are few real-time simulation tools. In DT-CPPS, due to the real-time manufacturing data being synchronised to the Digital Twin model, a comprehensive simulation app that contains different responsive scheduling strategies can be built. This app includes two modules, i.e. disturbance recognition and responsive scheduling, and the former acts as the input of the latter, as shown in Figure 8.

It first imports the real-time data processing results into the pre-set production plans. By comparing the current status of each process with the plans, recessive disturbances (e.g. time delay or lead of each process) and dominant disturbances (e.g. machine breakdown, order cancelling or insertion) can be achieved. Afterwards, the responsive scheduling engine embedded in the simulation app will take the disturbance information as the input parameters and invoke the scheduling rules/principles and engineered information/knowledge to make a decision on responsive scheduling strategies, such as no scheduling, time-shifting scheduling, moving-window rescheduling, autonomous predictive scheduling and so on. The algorithms for the responsive scheduling engine include knowledge-based reasoning (KBR), DNN and the non-dominant sorting genetic algorithm (NSGA-II). The integrated application of these algorithms is efficient, computation-saving and has a better optimum. After the scheduling strategy is made, CSF Digital Twin will decompose the strategy into specific commands and synchronise them with PSF through data interfaces. On that basis, smart parts will proactively interact and negotiate with smart resources to adjust their production plans in response to production disturbances. Meantime,

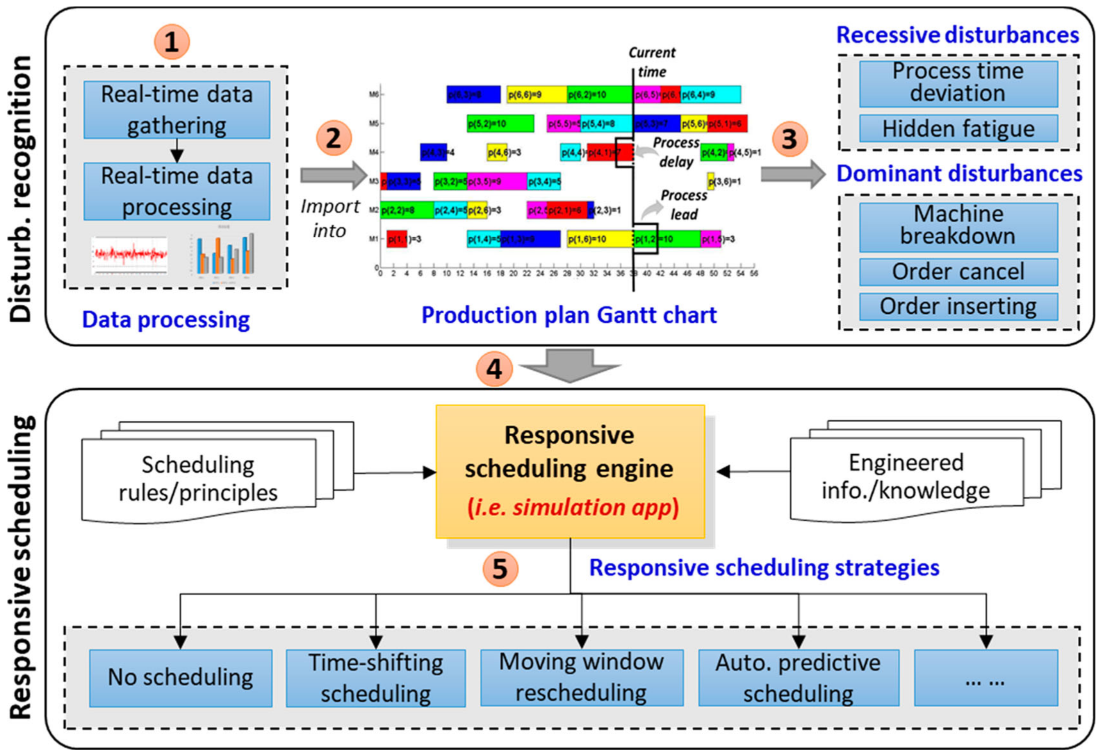

Figure 8. Responsive production scheduling strategies.

the adjusted information and knowledge will be visualised in shop floor Kanbans or mobile devices for transparent management.

7. Case study

Considering an example of a shop floor consisting of three CNC machine tools (two turning machine and one five-axis machining centre), two industrial robots with separate workstation buffers, one Automatic Guided Vehicle (AGV), one shop floor buffer, one Kanban and some other assistant resources, as shown in Figure 9. The shop floor undertakes the manufacturing of impeller prototype.

7.1. Configuration of DT-CPPS

First, the PSF configuration is performed including the smart parts (turbine blades prototype) configuration, smart resources (including machine tools, industrial robots and AGV) configuration and industrial network configuration, as shown in Figure 10(a). Every pallet maintains the RFID tag and embedded system device of a smart part. The static attribute information (e.g. ID, name, parameters and supplier in Equation (1)) is stored in the RFID tag, while the dynamic process information (e.g. quality, progress, location, availability and cost in Equation (1), and manufacturing operations flow in Equation (10)) and the simulation apps are stored in the local memory of the embedded system device. Besides, every control cabinet or like maintains the sensors, RFID reader, embedded system device and numerical control system of a smart resource to collect the real-time manufacturing data. The relevant data/information in Equation (4) is stored in the local memory of embedded system device. On that basis, these smart parts and resources are interconnected within a shop floor-level IoT platform, they can autonomously interact with each other concerning the static and dynamic information.

Second, the CSF configuration is performed from the logical mapping and cyber-physical mapping aspects. On one hand, every smart part and resource is modelled as a Digital Twin of itself, the PSF is mapped into a CSF and the whole physical production system is mapped into a cyber-production system. We establish the DT-CPPS by using Plant Simulation® software. The geometrical, physical, behaviour, performance and rule information of smart parts and resources are defined in detail. Figure 10(b) lists part of the interfaces of configuring the Digital Twin of smart resources.

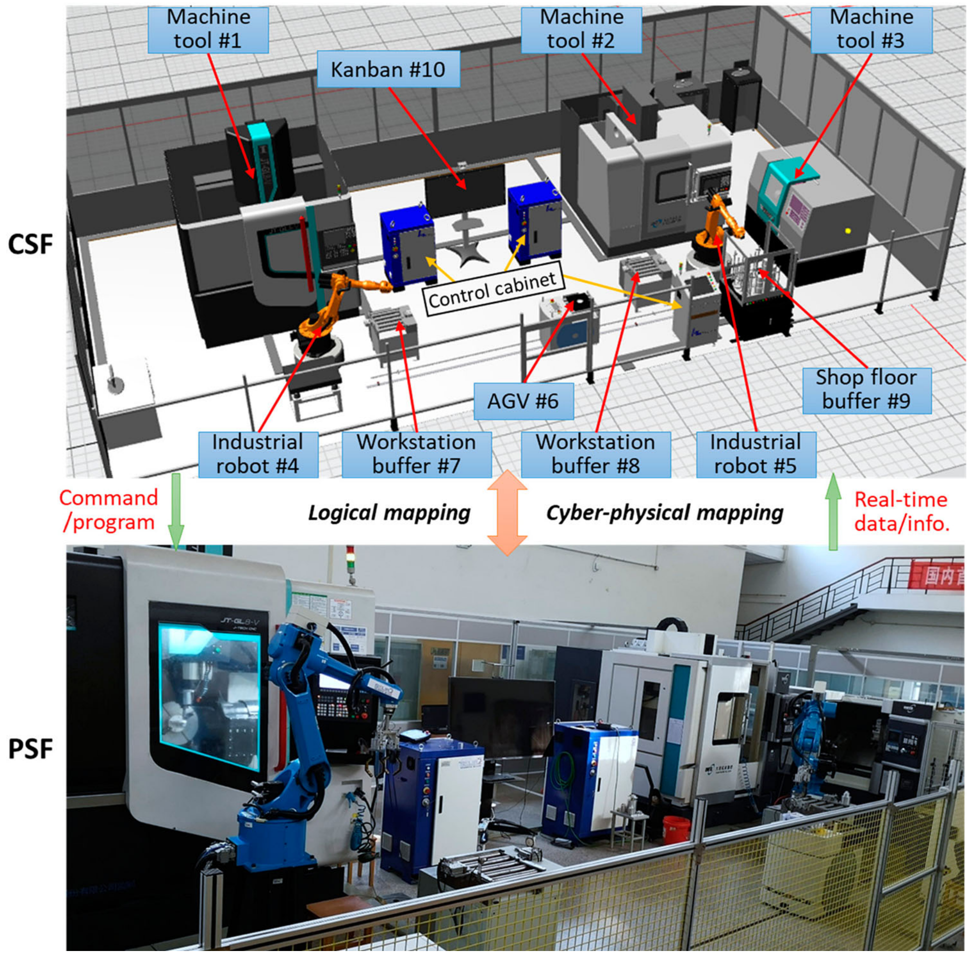

Figure 9. An example of DT-CPPS.

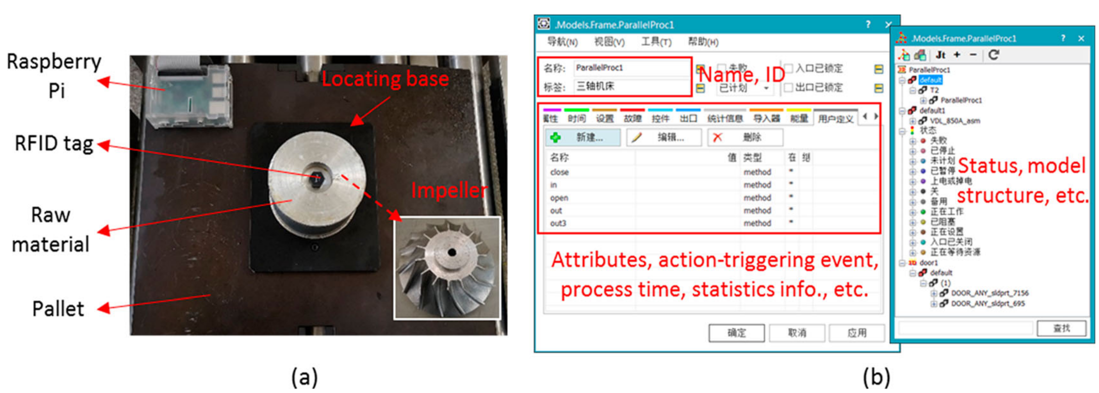

Figure 10. Smart part and resource configuration.

7.2. Operating of DT-CPPS

7.2.1. Operating flow

After configuring the PSF and CSF, the next step is to clarify the flow of autonomous manufacturing operations. Based on the operating flow of DT-CPPS in Figure 4, the specific smart resources allocation for sequential manufacturing operations is first initialised by using the HMM model in Section 6.2.2. The initial smart resources allocation solution is shown in Table 2. It is noted that this solution has the maximum probability for the impeller manufacturing than other allocation solutions according to the historical experience integrated in the HMM model.

Table 2. Process planning and resource allocation.

No.	Name	Content	Equipment
1	Turning	1.1 Cylindrical turning (rough); 1.2 Radial facing A (rough); 1.3 Convex plate turning (rough); 1.4 Impeller outline turning (rough); 1.5 Radial facing B (rough); 1.6 Location hole machining	CNC turning machine (#3)
2	Inspection	2.1 *In situ* quality inspection	Workstation buffer (#8)
3	Turning	3.1 Cylindrical turning (semi-finished); 3.2 Radial facing A (semi-finished); 3.3 Convex plate turning (semi-finished); 3.4 Impeller outline turning (semi-finished); 3.5 Radial facing B (semi-finished)	CNC turning machine (#2)
4	Inspection	4.1 *In situ* quality inspection	Workstation buffer (#8)
5	Transport	5.1 Transport the pallet-based smart part from workstation buffer #8 to workstation #7 by AGV	AGV (#6)
6	Milling	6.1 Impeller passage milling (semi-finished); 6.2 Impeller blade milling (semi-finished); 6.3 Blade root milling (semi-finished); 6.4 Impeller passage milling (finished); 6.5 Impeller blade milling (finished); 6.6 Blade root milling (finished)	Five-axis CNC machining centre (#1)
7	Inspection	7.1 *In situ* quality inspection	Workstation buffer (#7)
8	Transport	8.1 Transport the pallet-based smart part from workstation buffer #7 to workstation #8 by AGV	AGV (#6)
9	Turning	8.1 Location hole turning (rough); 8.2 Location hole turning (finished)	CNC turning machine (#2)
10	Warehousing	10.1 finished part warehousing	Shop floor

Note: The load/unload works from #7 to #1 and from #8/#9 to #2/#3 are performed by the industrial robot #4 and #5, respectively.

7.2.2. Operations control

In reality, since the raw materials (i.e. origin of the smart parts) are unloaded to the shop floor buffer #9, the smart resources in the DT-CPPS start interacting autonomously with each other and with the smart parts, the process of which centres on the initial operating flow in Table 2. Ideally, the smart resources will perform their separate responsible operations at the right time to achieve the required operation results. However, due to the smart shop floor is dynamical, flexible and autonomous, disturbances and exceptions may happen at any time. DT-CPPS should own strong autonomy to deal with that.

To enhance the transparency of the smart shop floor, real-time manufacturing data is collected roundly by the RFID, sensors, controllers and actuators in the shop-level IoT. Based on these real-time data, valuable information such as production progress and resource status can be achieved and visualised on the shop floor Kanban #10. For example, Figure 11 describes the monitoring interfaces of part flow and production progress. Figure 11(a and b) depicts the process transfer from the part view and machine view respectively. Figure 11(c and d) describes the whole progress of a part's manufacturing operations and the machining progress of each process at certain machine tool respectively.

Considering the real-time statuses of smart resources and processing time deviation of operations, the responsive production scheduling is taken as an example to describe the simulation-based manufacturing operations control. After calculating the real-time data of voltage, current and spindle speed based on a decision tree, a dominant disturbance is reasoned out by the CNC turning machine #3 that it has shut down. To keep normal the impeller manufacturing operations, #3 will broadcast forwardly a message that contains its shutdown information to the rest machine tools. Then all the rest machine tools will give their own responsive messages to #3 of whether it can undertake the task that should be performed by #3, at which time it can start the task, and how much time and cost it need to undertake the task. These responses are given according to the Digital Twin simulation results of the smart resources, and the simulation is based on the KBR, DNN, NSGA-II and other algorithms. On that basis, the responsive scheduling engine designed in Section 6.2.2 will give a scheduling strategy such as time-shifting scheduling, moving-window scheduling and others. In this case, only one part is manufactured in the smart shop floor, thus the responsive scheduling engine recommends that the CNC turning machine #2 will undertake the task of #3. It is rational because: (1) the machining parameters of #2 are superior to that of #3 and (2) #2 is currently accessible for the task.

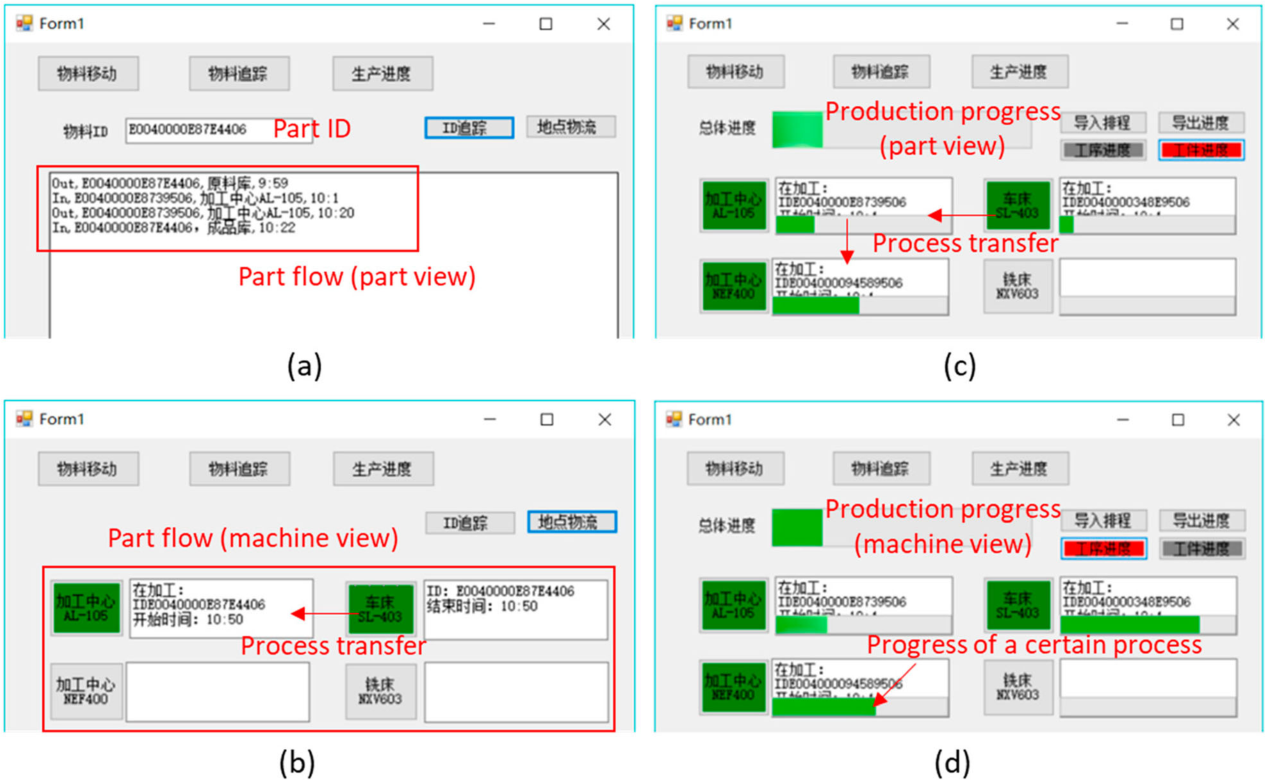

Figure 11. Production monitoring interfaces.

Except for the production scheduling, other operations control cases such as buffer congestion-induced deadlock resolution and AGV task allocation and optimisation are also solved by Digital Twin simulation-based methods. It should be noted that through cyber-physical interconnection, real-time data integration and sharing, and Digital Twin simulation, the centralised and human-intervened manufacturing operations control in traditional production systems can be replaced by a decentralised, autonomous and simulation-driven one in the DT-CPPS. On that basis, the goal of smart manufacturing that improving the transparency in shop floors and enhancing the real-time autonomous production control can be achieved.

8. Discussion

DT-CPPS is a dynamic production system enabled by CPS and Digital Twin technologies. It is a theoretical approach to apply new information technologies to suit smart manufacturing paradigms. From the view of manufacturing operations management, discussion on DT-CPPS can be focussed on three aspects.

8.1. Benefits

DT-CPPS bridges the gaps between PSF and CSF, and establishes the data synchronisation and interoperability channels to enhance the interactions between them. Within DT-CPPS, the real-time data perceived from PSF is transmitted to CSF for simulation and optimisation. The distributed Python apps and other software integrating various data processing methods are invoked to transform the data into engineered information for production decision-making. The decisions made are further fed back to PSF for follow-up control and management of manufacturing operations. DT-CPPS streamlines the monitoring, simulation, prediction and feedback control of manufacturing operations. Thus PSF becomes more flexible, transparent, efficient and autonomous.

8.2. Challenges

Although DT-CPPS implementation is a big vision in today's shop floors, especially for small and medium enterprises (SMEs) who want to reach the goals of smart manufacturing by using minimum investment and manpower. However, currently there are many limitations and challenges to the implementation of DT-CPPS. For example, the possibilities for synchronisation between PSF and CSF to establish closed loops seem to be somewhat insufficient, because of the immature development of industrial networks and out-of-step data computing technologies. Meantime, due to the heterogeneity of various resources in PSF, the data transmission and exchange among these resources pose a big challenge, i.e. the requirement of uniform data protocols and interfaces. AutomationML and MTConnect are the preliminary outcomes to deal with this challenge. Further work still needs to be done on the uniform data transmission and exchange protocols and interfaces. Another example concerns Digital Twin simulation. In practice, the fidelity and accuracy of current simulation models are less than satisfactory. More reasonable simulation models should be developed to improve the simulation results, not only in fidelity and accuracy aspects but also in complexity and efficiency aspects. Except for the above challenges, there are still some limitations on gathering, processing and storing big manufacturing data. The application of cloud computing, fog computing and edge computing methods should be further examined. We believe that with the rapidly developed information technologies and constant attention, these challenges and limitations will be solved sooner or later.

9. Conclusion

Smart manufacturing has becoming a prevailing research topic in the industry 4.0 environment. The shop floor is a basic carrier for implementing smart manufacturing. The real-time monitoring, simulation, prediction and optimisation of manufacturing operations are vital for improving the production flexibility and efficiency of the shop floor. In this paper, a DT-CPPS is proposed to build the interconnection and interoperability of PSF and CSF. The configuring mechanism, operating mechanism and real-time data-driven operations management of DT-CPPS are discussed in detail. Specifically, the DT-CPPS configuration is decomposed into the PSF configuration (i.e. smart part configuration, smart resource configuration and network configuration) and the CSF configuration (i.e. logical mapping and cyber-physical mapping). The DT-CPPS operating is described via a flowchart illustrating the interaction of PSF and CSF, together with the essential information interaction among them. The function modules for operations control of DT-CPPS are discussed in detail, including real-time manufacturing data processing, predictive machine sequencing model and responsive production scheduling strategies.

This paper discusses the concepts, framework, configuring and operating mechanism, and the real-time data-driven operations control of DT-CPPS. Since DT-CPPS is a conceptual basis for realising smart manufacturing in shop floors, future work should be devoted to: (1) human–machine–part autonomous interaction in a common working space, (2) analysis and optimisation of dynamic operating characteristics of DT-CPPS, (3) cyber security and information reliability for bi-directional data transmission between CSF and PSF, and so on. It is expected that DT-CPPS will act as a reference model for shop floors to head towards smart manufacturing.

Disclosure statement

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