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ORIGINAL ARTICLE

Cyber-physical integration for moving digital factories forward towards smart manufacturing: a survey

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Abstract

The current study on digital factory (DF) meets some problems, such as disconnected manufacturing sites, independent digital models, isolated data, and non-self-controlled applications. In order to move current situation of DFs forward towards smart manufacturing, this paper attempts to present an overview of current digital situation of factories, and propose a systematical framework of cyber-physical integration in factories, with consideration of the concept of digital twin and the theory of manufacturing service. Particularly, the proposed framework includes four key issues, i.e., (a) *fully interconnected physical elements integration*, (b) *faithful-mirrored virtual models integration*, (c) *all of elements/flows/businesses-covered data fusion*, and (d) *data-driven and application-oriented services integration*. The corresponding implementable solutions of these four key issues are discussed in turn. As a reference, this paper is promising to bridge the gap in factories from current digital situation to smart manufacturing, so as to effectively facilitate their smart production.

Keywords Cyber-physical integration · Smart manufacturing · Digital factory (DF) · Digital twin · Manufacturing service

1 Introduction

To meet the inevitable trends and thereafter derived requirements of socialization, personalization, servitization, intelligence, and green in manufacturing, it is necessary to make smart manufacturing come true gradually based on current digital situation of factories and then to achieve therein smart production operation and management [1, 2]. Along with the maturity and applications into manufacturing of some new-emerging information technologies (ITs), such as cloud computing (CC), Internet of things (IoT), big data, and artificial intelligence (AI), it makes both chances and challenges for industry and academia [3]. However, the one of the most typical challenges is how to apply those new ITs comprehensively to cope with the aims of manufacturing industry around the world as indicated above. In response to this context, different countries have come up with their own national strategies [4], for instance Industry 4.0, Industrial Internet, cyber-physical system-based manufacturing, and Made in China 2025. After analyzing those national strategies carefully, it is found that although the background is different, there exists one common goal, namely to realize the interconnection and interoperability between physical world and cyber space of manufacturing so as to achieve smart manufacturing. Specifically, how to bring out the cyber-physical integration is the one of the most important hurdles [5].

In order to solve the main bottleneck of cyber-physical integration in different scopes, step by step from manufacturing sites to workshops, and even to factories, the concept of digital factory (DF) [6, 7] is proposed and discussed for years. Scholars and practitioners have carried out a large number of theoretical researches and valuable techniques on DF. These studies analyzed the issue of physical-cyber integration to a certain extent either in theoretical view or in technical view, and put forward some corresponding solutions. However, no matter from which aspect, the core issue of cyber-physical integration to be addressed based on

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current digital situation of factories could be exactly classified into two stages. In view of the production-related data in DF, the first one is *physical data integration*, and the second one is *cyber-physical data integration*.

The first stage of *physical data integration* means collecting massive data from the manufacturing sites in physical world of factories and transmitting those data into the information systems deployed in factories. In recent years, many new ITs have been applied. For examples, IoT-related technologies and devices, e.g., radio frequency identification devices (RFID), Zigbee, and various kinds of advanced sensors, are used to collect different types of data concerning the full production lifecycle. CC-related technologies, e.g., Hadoop and MapReduce, are adopted to store and process the collected data [8]. AI technologies such as deep learning could support manufacturing data mining and its value creation. Moreover, service-oriented technologies, e.g., service-oriented architecture (SOA) and web service, help to achieve the service encapsulation and on-demand use of manufacturing data. As a result, *the manufacturing service-based approach devoting to realizing data integration, especially the application of big manufacturing data* [9] *in factories, is proved to be an effective way and trend*. However, the existing studies just concern *SOA-based crusade of an information system deployed in factories*, or *service-based integration of some deployed information systems*. Unfortunately, as manufacturing services are inseparable from data, just those finite data in the related information systems are considered, while not including the real-time collected data from the physical manufacturing sites. It also lacks the presentation, consideration, and interaction of the real-time collected data, thus it is really hard to reflect both physical world and cyber space of factories relying on the existing theories and methods of manufacturing services. Furthermore, when applied manufacturing services to address some decision-making problems in the actual production operation processes, how to comprehensively reflect the interaction, iteration and fusion between the real-time collected data from physical world and other data existing in these deployed information systems which are both involved in manufacturing services? How to depict and support *co-existence*, *co-evolution*, and *co-simulation* between complex dynamic production activities in physical world and the corresponding data and models in cyber space of factories? Those are the key points to determine whether manufacturing services could be further applied into DFs so as to improve production operation and management.

The second stage of *physical-cyber data integration* signifies to add value and efficiency of both the data collected from the physical manufacturing sites and the data generated or existing in these deployed information systems. For these multi-sourcing heterogeneous data either from physical world or in cyber space of factories, digital twin [10] is being widely concerned. It is an effective way to realize the real-time interaction and integration between physical world and cyber space, and has the following three main features [11, 12]: (a) It integrates various types of data of the physical objects, and it is the faithful mirror of the physical objects. (b) It is co-evolutionary with the physical objects, accompanied by the constantly updating of real-time data collected from the physical objects. (c) Based on virtual models, it could not only describe the physical objects, but also optimize the physical objects. Actually, digital twin has been successfully applied into the defense, aerospace, and other important areas. For example, the U.S. Department of Defense introduced the concept of digital twin to the health maintenance of aerospace crafts [13], and defined it as an integrated simulation process of virtual models mirrored the whole lifecycle of the physical crafts. Grieves et al. combined the physical systems with their equivalent virtual systems as a comprehensive system based on digital twin to study fault prediction method, and validated it in the related systems of NASA [14]. Parametric Technology Corporation (PTC) established a real-time connection between the virtual world and the real world of its products based on digital twin, to provide customers with efficient after-sales services based on digital twin data [15]. Siemens put forward the concept of digital twin to help manufacturing enterprises build a production system model in cyber space, in order to achieve the entire digital process from product design to manufacturing in physical space [16]. These mentioned typical examples and applications all indicate that digital twin is a promising effective method to achieve physical and cyber data integration and fusion of factories.

Therefore, combining the concepts of digital twin and manufacturing service, their complementarity and interdependency pave the way for addressing the core issue of cyber-physical integration based on current situation of DFs. This paper attempts to propose a systematical framework of cyber-physical integration with consideration of these two concepts, in order to move current DFs forward towards the aims of smart manufacturing. The remainder of this paper is organized as follows. Section 2 describes state-of-the-art of DFs. To reveal the gap between current situation of DFs and the objectives of smart manufacturing, Section 3 analyzes and summarizes the characteristics and aims of pursuing smart manufacturing in factories. Thereafter, to narrow this gap, a systematical framework of cyber-physical integration based on digital twin and manufacturing service and the derived operational mechanisms, as well as the corresponding enabling technologies, are presented in Section 4. Finally, Section 5 concludes the full text.

2 State-of-the-art of digital factories

In order to build a DF, to implement digitalization and virtualization in DFs, and to achieve its operational improvements in final, the existing relevant studies are analyzed carefully from the following four aspects.

2.1 Physical connection and data collection

Physical connection refers to making factories and their production processes have the ability to collect more data from the physical manufacturing sites through perception of separate manufacturing resources, thus supporting data acquisition and transmission from the underlying equipment to MES, and even supporting instruction release and control from MES to the underlying equipment. The related studies can be divided into the following two stages.

2.1.1 Perception and access of relevant elements

With the expansion of digital degree and scope in factories, data collection from the physical manufacturing sites depends on intelligent numerical control (NC) equipment itself, or using intelligent acquisition devices with the corresponding automatic acquisition technologies. Therefore, the perception and access of production-related resources and other elements for their data collection becomes the core of the integration and interaction between the physical manufacturing sites and the information systems.

Perception and access of different production-related equipment Traditional production-related equipment can be divided into NC equipment and non-NC equipment. For a single NC equipment, it mainly relies on a specific acquisition device, such as the embedded PLC acquisition module, to collect and read status information of the NC equipment and its running. For multiple different NC equipment, the perception and access mode is developed from early direct numerical control (namely early DNC) to current distributed numerical control (DNC) network systems [17]. In those DNC network systems, the sub-system of manufacturing data collection (MDC) could support five kinds of acquisition methods, including direct acquisition, adding the dedicated acquisition hardware, barcode scanning, special PLC-based acquisition, and human-computer interaction. To date, those DNC network systems could achieve both the compatibility of hundreds of control systems and the compatibility of various hardware interfaces and communication standards. As to the type of non-NC equipment, the traditional acquisition method is based on large number of electrical sensors, strain gauges, fiber grating sensors, etc. However, this method could just measure finite number and accuracy of physical parameters of the non-NC equipment [18].

Perception and access of other production-related elements A factory including the production activities in it could be treated as a complex eco-system [19], which is composited by all kinds of heterogeneous production-related elements, such as manufacturing machines and auxiliary equipment, materials, semi-products, and operators, only to realize data collection of the production-related equipment, cannot support the further optimal operation in DFs. Considering all kinds of heterogeneous production-related elements in DFs, there are some technologies applied for collecting the real-time data of activities from the physical manufacturing sites, for examples data collection based on automatic identification technologies, online measurement technologies and corresponding digital detection equipment, and information systems integration [20]. Nowadays, RFID, wireless sensor network (WSN), and other IoT-related technologies, as well as the corresponding specific devices, are more and more used. However, due to the shortages of incomplete elements access, finite collected data, and separate acquisition methods, it is still hard to make sure system-wide interconnection and interoperability considering all of heterogeneous elements and the related multi-sourcing data.

2.1.2 Processing of the collected data

Processing of the data collected from the physical manufacturing sites is to provide reliable data for status monitoring and health management of elements, and even operation optimizations of the entire factories. However, dynamics and complexity of the physical manufacturing sites result in some characteristics of the original perceived and collected data. The characteristics include multiply sources, wide types, and high redundancies. Then, unreliability and uncertainty in transmission process of the collected data usually cause some typical problems [21], such as data missing, packet loss, conflict, out-of-order, and delay. Facing the above characteristics and typical problems, processing of the collected data is mainly classified into data cleaning and data fusion operations.

Data cleaning It aims to ensure higher quality of the sources and flows of the collected data. As aforementioned, most of data collections mainly rely on DNC network systems, RFID, and WSN. There are lots of data cleaning models for the data collected by these perception and access methods in the existing studies [22]. For example, space or time smoothing mechanism-based model, machine learning-based model for misreading problems of the collected data, path constraint-based model for out-of-order problems of the collected data, and prepared path matching-based model for dirty data. However, these models have better performance for cleaning the static data, rather than considering the frequent transition, distributed processing, time delay, and other dynamic characteristics in the data collection and transmission processes with multiple data sources.

Data fusion It is an operation to generate meaningful information from the original collected data. Besides the widespread applications of RFID in factories, WSN is also increasingly playing an important role in monitoring the ever-changing environment in factories. The existing related researches focus on two aspects, i.e., data fusion within WSN and heterogeneous data fusion between RFID and WSN. For the aspect of *data fusion within WSN*, because of different configuration environment of sensors and therein different monitored objects, there are four kinds of architectures adopted, i.e., the centralized, distributed, mixed, and heuristic architectures. As to the other aspect of *heterogeneous data fusion between RFID and WSN*, the existing related discussion refers to three kinds of architectures, i.e., heterogeneous wireless integrated networks, distributed intelligent node networks, and smart sensing tag networks.

2.2 Digital/virtual models and simulation

Digitization stimulates feasibility verification of production activities and optimization of production management through the relevant virtual models building and simulation. The modeling ability is an important criterion to measure the digitization degree of DFs [23]. Virtual models are treated as another kind of existence of data, and would generate much valuable information by their simulation processes. Considering different modeling objects and virtual models, the existing related studies are analyzed from the following two aspects.

2.2.1 Virtual modeling and simulation for DFs

Considering various elements and entities as well as the real production operation processes in DFs, it leads to differences in both variety and function of virtual models of DFs. There are almost the following three kinds of virtual modeling and simulation applications. (a) *For production layout* [24], there are two categories of simulation optimization, either based on mathematical models and algorithms or based on virtual models. (b) *For specific entities* [25], one of the most typical entities modeling is based on digital prototyping [26] in order to achieve structure and performance optimization, assembly simulation, mechanical dynamics simulation, multi-dimensional display of the entities' appearance and function, and so on. (c) *For production processes* [27], it is to create the relevant entities classes with their logical relationships in the modeling and simulation environment, thus to carry out simulations to verify the details of production processes and to test production plans, as well as to balance production lines.

2.2.2 Classification of DFs-related virtual models

Most of DFs-related virtual models take on the modeling and simulation analysis for the preliminary production operation. The existing typical virtual models can be mainly classified into the following categories. (a) *Product models* [28] extract the product structure and shape characteristics through methods of mapping, abstract and others. (b) *Resource geometric models* describe size, shape, and trajectory of the relevant elements to achieve the interference tests for production processes and the simulations of time or cost. (c) *Resource physical models* consider physical factors based on resource geometric models [22]. Most researches focus on the modeling of equipment and personnel, and the simulation to discuss physical parameters varying and compensation of equipment. (d) *Production capability models* depict production capability and characteristics of the systems. They are used to both describe the feasibility of a specific product design and evaluate the detail production process with low cost under a particular manufacturing system [29]. (e) *Process models* link process-related parameters to design attributes of a product and reflect interaction between the models of the production process and the corresponding product [30]. Therefore, due to different purposes of simulations, the existing virtual models are such independent that it still needs a set of systematic modeling methods and unified standards for models integration [31], so as to enrich DFs-related virtual models to support the faithful mirror and meet various application requirements of the dynamic production operation processes.

2.3 Data and information systems integration

Data integration is not only the inevitable trend and requirement of DFs, but also the essential premise for comprehensive applications of those information systems deployed in DFs. In order to overcome information islands and improve management efficiency, more and more researchers pay attention to data or information integration in favor of much broader sharing and wider applications.

2.3.1 Data/information integration in cyber layer

The existing relevant researches mainly reveal the data or information integration and sharing in cyber layer, which relies on a certain platform integrated with some information systems [32]. In light of different scopes of data integration in DFs, it can be divided into the following five cases. (a) *Integration of different deployed information systems*, e.g., the integrations between PDM and ERP, between PDM and MES, and between ERP and SCM. (b) *Integration among different modules within the same one deployed information system*, e.g., integration among fieldbuses and integration between fieldbus and industrial Ethernet. (c) *Data conversion* *between different information systems or between different CAx software*. (d) *Integration between the internal ERP and the external e-commerce platform* [25]. (e) *Integration between software and hardware systems*, e.g., the integrations between ERP and bar code system, and between ERP and automated storage and retrieval system [33]. However, with the increasing demand for information sharing and application, it is difficult to adapt to the requirements just integrating the data or part of real-time data in the deployed information systems. The comprehensive integration covering different information systems and running through upstream and downstream of business processes is becoming the inevitable trend of digital improvements in DFs.

2.3.2 Data integration from physical layer to cyber layer

Driven by the rapid development and gradual applications of ITs and automation technologies in DFs, various kinds of advanced sensors and data acquisition devices provide the capability to collect massive real-time physical data. The environment of production operation in a DF is complex and changeable, thus the real-time data collected from physical world is not enough [34]. Actually, the existing ERP, PDM, CAx, and other deployed information systems cannot support the bi-directional interconnection and integration between the data collected from physical layer and the data existing or generated in cyber layer [35]. It is hard to ensure the sharing of all of data which could cover each production stage and suit various application requirements. Furthermore, due to the integrated data either in cyber layer or collected from physical layer that would be used across different information systems and multiply production stages, it needs to unify the existing data modeling methods. In general, the collection and integration of real-time data from physical layer is relatively less considered. The lack of data integration from physical layer to cyber layer, and especially the lack of real-time interaction and fusion between these two layers of data, both result in separation between the real production processes in physical factories and the operation management in cyber space.

2.4 Data-based production operation modes and management methods

The high-efficient production operation and management is the ultimate goal of DFs. No matter the efforts for their digitalization upgrading based on physical connection and information integration, or the efforts for their virtualization improvement based on digital/virtual factories modeling and simulation, they collectively push forward the continuous evolution of production operation modes and management methods.

2.4.1 Improvement of production operation modes

The production operation in a factory faces a variety of optimization issues, including product quality control [36], production planning/scheduling and control [37], fault diagnosis [38], and predictive maintenance. To solve those issues, most of the existing studies modeled the optimization problems based on limited data, and then figured them out by some analytical methods. Most of them are carried out with the common procedures, which include the in-order steps of *problem analysis*, *modeling*, *algorithm design and solution*, *and optimized control*. As the complexity of production operation increases, the traditional operation modes are of poor adaptability because of the high-complexity of problem models and algorithms. After big data, IoT, and other new ITs applied into manufacturing, the approaches begin to be converted. Firstly, enough data are collected by intelligent equipment and sensors, which are reflecting the real-time status of production operation. Then, some correlations and knowledge are mined from those collected data, some dynamic evolution rules of those data are also studied to reveal and find the potential information. Finally, the potential information stimulates the active and predicted production operation mode [39]. That is to say, this mode is based on the procedures of *data and correlation mining*, *dynamic evolution*, *simulation and prediction*, *and intelligent control.*

2.4.2 Evolution of production management methods

The evolution of production management methods has undergone several typical stages. So far, service-based production management [40] is paid more and more attention. With the continuous development of digitalization degree in DFs, the service-based method could effectively integrate the resources and information in both physical layer and cyber layer, and then pave the way to achieve high-efficient and precise production management. The typical evolution stages are listed as follows [41]. (a) *Based on manual management*. The production factors and plans related data are recorded in the form of papers. To obtain the required data in this stage is of low quality, efficiency and accuracy, and poor real-time performance. (b) *Based on an independent information system*. Some data in the specific independent information system can reflect the physical real-time status, but there exist characteristics of complex relationships, high-degree correlations, and data redundancy. (c) *Based on the integrated information systems and services*. The relevant resources and the corresponding models and data could be organized effectively based on some information systems integration in the form of services. It is the basis of data integration, fusion, and further utilization for optimal production management.

2.5 A brief summary

There summarizes the following four findings corresponding to the above four aspects of analysis on DFs.

For *physical connection and data collection*: At the underlying manufacturing sites in factories, it is an extremely complex situation consisting of various machines, materials, humans, and other heterogeneous elements. Even though it achieves physical connection of some production-related elements in DFs, but it lacks technologies for system-wide physical connection and even interconnection of all of relevant elements, as well as the corresponding general device which cloud support both perception and access of heterogeneous elements and processing of all kinds of data collected from multiple sources.

For *digital/virtual models and simulation*: The existing researches mainly focus on building models of the systems and processes, or simulation analysis of the geometric models of some specific elements. However, in order to depict and reflect all of the real production-related activities, behaviors, rules, and constrains in factories, it still lacks the comprehensive faithful-mirrored models, and is also without consideration of the real-time data in their simulation processes. It is necessary to carry out the multi-dimensional integrated models to cover both the geometric information of each element as well as its behaviors, rules, constrains, and others.

For *data and information systems integration*: The situation of information integration and sharing depends on the related information systems deployed in factories. The existing researches mainly focus on data integration and sharing in the deployed information systems, such as manufacturing execution systems (MES), enterprise resource planning (ERP), and computer-aided process planning (CAPP). Due to lack the device for system-wide interconnection of all elements, they are almost with rare consideration of the real-time collected data from the physical connected elements. There is still a long way to go for realizing the system-wide data fusion and interoperability of the integrated data from both physical and cyber layers.

As to *data-based production operation modes and management methods*: As different ITs developed and applied into manufacturing, production operation and management in factories have been changing from the traditional procedures of "*problem analysis*, *modeling*, *algorithm design and solution*, *and optimized control*" to the innovative procedures of "*data and correlation mining*, *dynamic evolution*, *simulation and prediction*, *and intelligent control*". No matter how the mode changes, it always depends on the data and models which are reflecting real processes and status of production operation. However, physical elements and information systems are separate, and multi-dimensional integrated models are scarce. They both result that management in cyber space and operations in physical production are out of sync and consistence, and restrict the accuracy of their operation optimizations.

3 Aims and characteristics of smart manufacturing in factories

By the innovation of ITs applied into manufacturing, smart manufacturing is both the trend and result of sustainable development of current DFs. The concept of smart factory (SF) is accordingly derived, representing the aim to carry out smart manufacturing in factories. To date, there is no consistent definition about SF, while there are some concepts similar to it, e.g., the ubiquitous factory [42] and factory-of-things [43]. According to the selected typical one of various definitions on SF [44], the *smartness* of a developed DF comes from data as well as the ability to carry out the process of "*Data-Information-Knowledge-Wisdom*" (DIKW) [40]. More specifically, it uses advanced sensors to collect data. Data and models provide real-time information. Information is then used to run the factories better and generate knowledge. When knowledge is used across factories and enterprises, this is where smart manufacturing and wisdom are achieved [36, 40]. Exactly, it is similar to the coming procedures indicated in Section 2.4.1. Therefore, the main aims of SF are marked in brief as information transparency, autonomous control, and sustainable manufacturing. Indeed, all of these depend on data, actually, the big manufacturing data.

However, there also is no uniform description and classification of the characteristics of SF. Based on the above four findings summarized on current situation of DFs, the relevant characteristics that are pursued in a SF are correspondingly discussed in the following items.

(1) *Physical separation but ubiquitous interconnection*. Ubiquitous interconnection with scalable and modular structure is to make real production be with context-awareness and collaborative initiative by physical data collection, interaction, and even interoperation. It means that the autonomous decision making and sustainable production take place by gathering, exchanging, and using information transparently anywhere and anytime with networked interaction between man, machine, materials, and systems [39, 41].
(2) *Systematic virtual models-based digital counterpart*. The digital counterpart of factories and therein productions based on systematic virtual models is desired to support reliable and synchronous co-simulation, and then closed-loop correction and control. The co-existence and co-simulation of the digital counterpart include operations of virtual commissioning, the real line commissioning, and running/operation in reality [45].
(3) *Thorough integration and transparent fusion of all of data*. Considering all of data both perceived from physical world and existed in cyber space, as well as generated iteratively in their co-evolution process by their bi-directional interoperability, the core to achieve smartness is thorough integration and transparent fusion of all of data.

Moreover, the co-evolution of both the physical factory and the digital counterpart is also as coordinated evolution covering products, processes, and production systems [46].

(4) *Value creation and efficiency adding of data by its utilization*. It takes copious and diverse data to produce information and knowledge, as well as add its value from which knowledge is derived to make robust decisions. In view of integration, adaptation, and replacement, it could scale up or down the production capacity and efficiency to satisfy uncertain demands or to respond flexibly to unpredictable disruptions and failures.

After the comparison between the aims of smart manufacturing in factories and their current digital situation, some main features of the gap between these two are pointed out as indicated in Table 1. All of these features and issues of the gap are summarized as *cyber-physical integration*.

4 How to bridge the gap of cyber-physical integration?

For the sake of transition from traditional information integration to cyber-physical integration in factories, so as to provide theoretical and technical supports for improving the intelligence or smartness, efficiency, and precision of their production operation and management, a systematic framework based on digital twin data [38] and manufacturing service is proposed in this section.

4.1 Framework of cyber-physical integration in factories

In view of the gap features indicated in Table 1, a framework of cyber-physical integration in factories for the aims of smart manufacturing is composited of the corresponding four layers of integration as well. As shown in Fig. 1, the four layers and their relationships in the proposed framework are illustrated respectively as follows.

(1) Fully interconnected physical elements integration

Fully interconnected physical elements integration means to realize the connection and even interconnection, and then to carry out the comprehensive integration, thus to support self-control with context-awareness, for all of heterogeneous production-related elements existing at the manufacturing sites or in the production processes, i.e., machines, robots, materials, parts/semi-products/final products, and participators. It is in order to provide the real-time relevant data from multiple dynamic sources of the physical manufacturing sites as much as possible for the subsequent virtual models integration and the overall data fusion. Mainly based on the architecture of CPS, new intelligent perception technologies and devices, heterogeneous networks convergence technologies, and others, it aims to carry out the significant vision of heterogeneous production-related elements which are separate in physical but aggregate in logical.

(2) Faithful-mirrored virtual models integration

Faithful-mirrored virtual models integration is to come up to the integration of all of models related to factories and therein production systems and processes, simultaneously considering the real-time perceived data by physical interconnection, so as to provide both enough models and reliable data for the simulation, analysis, and visualization required in production management. Due to ensure the virtual models be as the mirrors of physical factories as well as their production operation processes, those integrated virtual models are classified into different categories, i.e., geometrical models and physical properties models of production-related elements, response models of production-related behaviors, and logical models of production-related rules. They finally form the faithful-mirrored virtual factory models corresponding to the physical one, which is the digital counterpart after coupling such complicated virtual models in multiple dimensions. Furthermore, looking forward to the virtual-real interaction more than only mirroring in their co-simulation and synchronous operation processes, how to make sure of the real-time interaction and control between the digital counterpart and the physical world attracts much more attention.

(3) All of elements/flows/businesses-covered data fusion

All of elements/flows/businesses-covered data fusion refers to such big manufacturing data both perceived from physical world and existed in cyber space, as well as generated iteratively in their co-evolution processes, which is derived after the multi-layer integrations and co-evolution based on the multi-source data generated by both fully interconnected physical elements and faith-mirrored virtual models. As a result, the indicated big manufacturing data covers and fuses all of production-related elements, flows, and businesses. In detail, it consists of the real-time data perceived from the physical production field, the simulated data generated from the virtual mirrored models, the prescriptive and descriptive data existing in the deployed information systems. Along with the continuous processes of integration, interaction, iteration, and evolution of the big manufacturing data, the result of this dynamic evolutionary reaction is called as *digital twin data* [41], after introducing the concept of digital twin. Actually, the co-evolution process after multi-layer integrations of both fully interconnected physical elements and faith-mirrored virtual models does make a big difference to the traditional industrial information integration and data fusion. Inevitably, there derives a series of laws and a systematical theory

Table 1 Comparison between current digital situation and the further aims of smart manufacturing in factories

Analysis aspects	Current DFs	Aims of SFs	The gap features
Physical connection and data collection	*Physical connections in part* of production-related elements, which are separate and independent in their location	*Physical separation but ubiquitous interconnection* supporting data collection, interaction, and interoperation, so as to make production be with *context-awareness and collaborative initiative*	*Fully interconnected physical integration* of any production-related elements (e.g., equipment, materials, humans, and environments,), and their corresponding behaviors and rules
Digital/virtual models and simulation	*Specific digital modeling and independent simulation* of some elements, production systems, and processes	*Systematic virtual models-based digital counterpart* of factories and therein productions supporting *co-simulation* (both reliable and synchronous), *closed-loop correction*, *and control*	*Faithful-mirrored virtual models integration* considering multi-dimensional models which include geometrical and physical properties models of elements, response models of behaviors, and logical models of rules.
Data and information systems integration	*Information integration and data sharing in part* of information systems deployed in factories	*Thorough integration and transparent fusion of all of data* both perceived from physical world and existed in cyber space, as well as generated iteratively in their co-evolution process	*All of elements/flows/businesses-covered data fusion* both accompanying with and resulting in the dynamic generation, iteration, and evolution of big manufacturing data
Data-based production operation mode and management method	*Few data assisting to analysis and decision making* related to product design and manufacturing	*Value creation/adding of data* by its utilization based on physical-cyber consistency and synchronization, for *operation optimizations* in factories	*Data-driven services integration and application* by the on-demand matching and utilization of services for the real production

need to be explored on the dynamic generation and evolution phenomenon of digital twin data in the operation process of factories.

(4) Data-driven and application-oriented services integration

The dynamic fusion process of digital twin data not only reflects the running conditions of physical elements and virtual models, but also keeps driving and affecting the iterative running processes of both physical production and virtual simulation respectively as well as the co-evolution between these two parts. The dynamic generation and evolution phenomenon of digital twin data covering all of elements, flows, and businesses in factories is also a process along with value creation and efficiency adding of those data, which also could be presented in the form of manufacturing services. Considering the valuable data mined from digital twin data to manufacturing services, an innovative method for production operation and management in factories is brought out. That is data-driven and application-oriented services integration, which is divided into two stages of integration for operation optimizations in factories: the underlying *digital twin data-driven services integration* and the subsequent *integrated services-driven application*. In one hand, digital twin data-driven services integration is resulted from the integration in a certain extent of software/hardware and the deployed information systems in factories, which is based on physical elements integration, virtual models integration, and the dynamic fused digital twin data in their co-evolution processes. In another hand, the integrated services-driven application is the supply-demand matching issues of manufacturing services [47] after demand decomposition and application analysis.

4.2 Operational mechanisms based on cyber-physical integration

Respectively and complementally, Fig. 2 depicts the derived closed-loop operational mechanisms based on the proposed layered framework of cyber-physical integration in factories. It includes the following ten mechanisms which are collectively supporting the circular stream of all of the production-related data.

Mechanism (1): Tasks decomposition by analysis on real demands, provides factories the input of decomposed tasks which could be matched and executed by the primitive manufacturing services.

Mechanism (2): Operation of the fully interconnected physical factories driven by uncertain demands and dynamic tasks gives rise to generation of the perceived data from physical factories.

Mechanism (3): Co-simulation of the faithful-mirrored virtual models accompanied with the operation in physical factories leads to generation of the simulated data from virtual models based on the virtual-reality interaction.

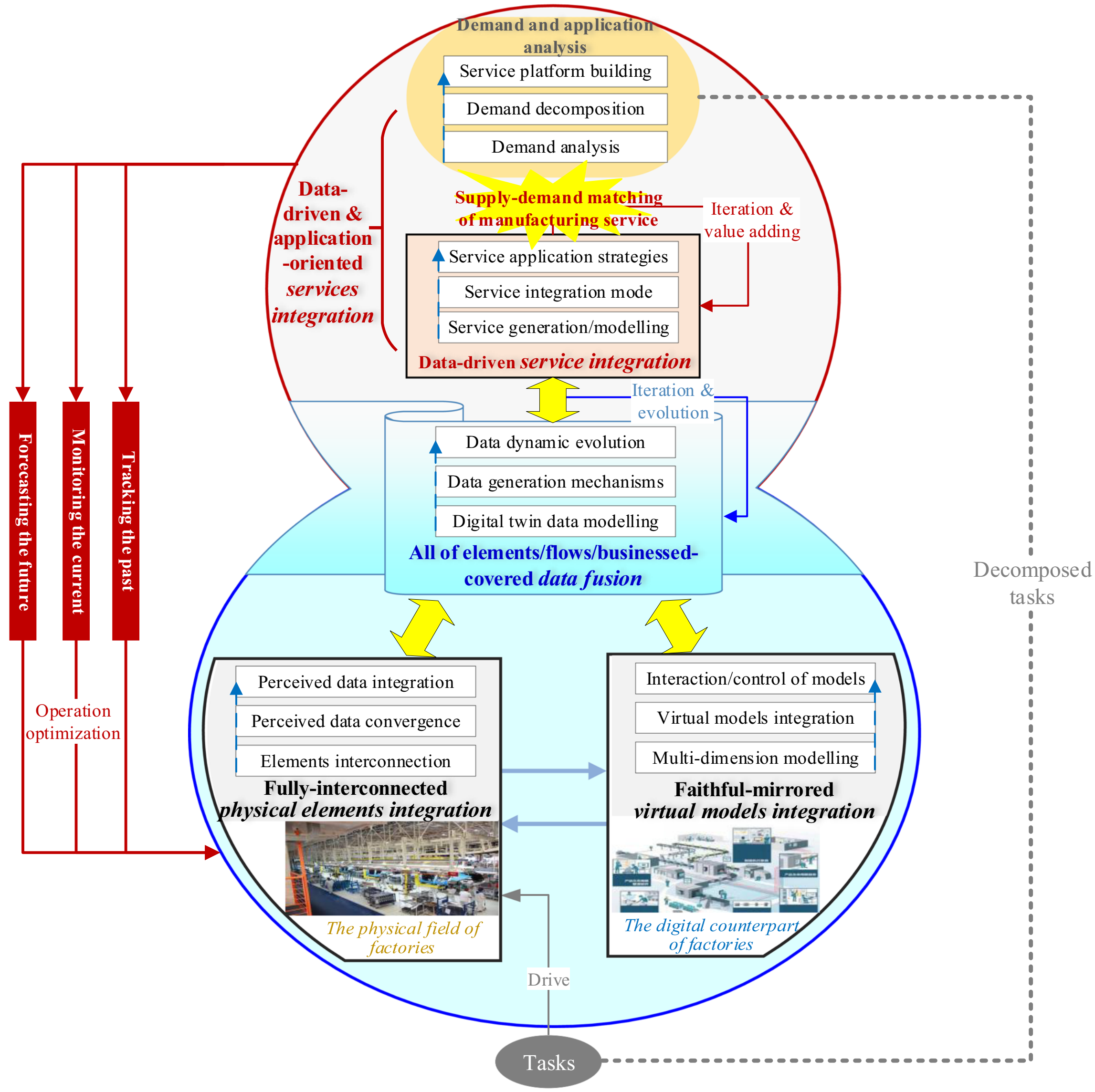

Fig. 1 Framework of cyber-physical integration in factories

Mechanisms (4) and (5): Transmission of both the perceived data from physical factories and the simulated data from virtual models offers enough constituent data of digital twin data.

Mechanism (6): Dynamic generation of digital twin data is derived by continuous interaction, iteration, fusion, and evolution among the perceived data from physical factories, the simulated data from virtual models, and the descriptive and prescriptive data existing in the deployed information systems, etc.

Mechanism (7): Integration of manufacturing services is facilitated along with dynamic evolutionary digital twin data, so as to result in a different mode of services application in the production operation and management processes.

Mechanism (8): Correlation mining of manufacturing services is caused by data mining-based value creation and adding of digital twin data.

Mechanism (9): Supply-demand matching of the integrated and correlated manufacturing services improves the efficiency of services application in production with consideration of digital twin data covering all of physical elements, flows, and businesses.

Mechanism (10): Digital twin data-driven services application through supply-demand matching makes a big difference to achieve operation optimizations in the whole production lifecycle of factories.

In summary, the above closed-loop operational mechanisms collectively portray and discuss both the bi-directional interconnection between physical layer and cyber layer of

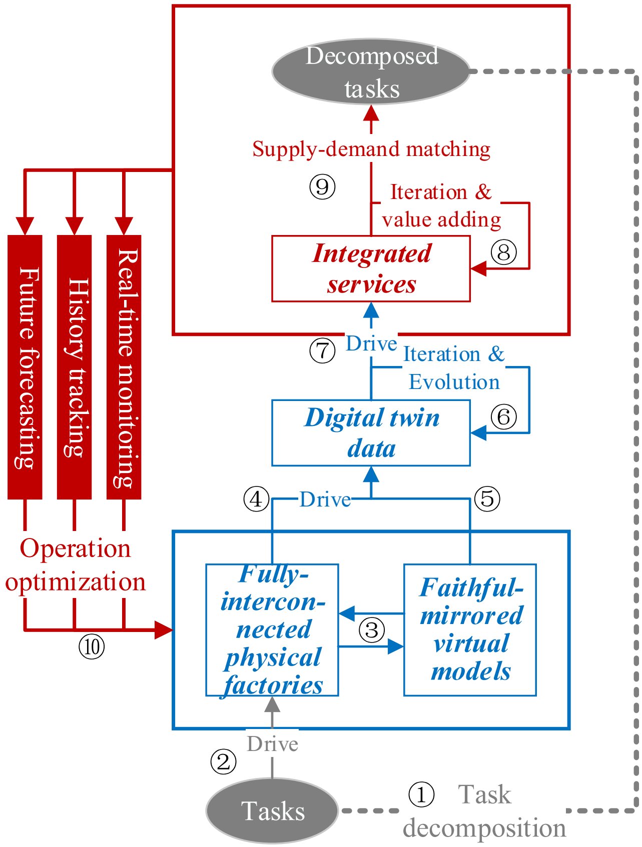

Fig. 2 Closed-loop operational mechanisms based on cyber-physical integration

factories, as well as the digital twin-based co-existence and co-evolution between the real factories and the corresponding digital counterparts.

4.3 Enabling technologies to achieve cyber-physical integration

Aiming at the proposed framework and the corresponding operational mechanisms, the following technologies effectively enable to bridge the gap of cyber-physical integration from current digital situation to the aims of smart manufacturing in factories.

4.3.1 Technologies for fully interconnected physical elements integration

Interconnection technologies of all of relevant heterogeneous elements in physical factories There are three aspects of interconnection technologies need to be addressed:

– features extraction methods of all of heterogeneous elements and the corresponding perceived data,
– multi-source sensors-based protocol analysis technology and collaborative measurement technology, and
– fusion networking and layout optimization methods of multi-site heterogeneous sensors.

Dynamic convergence and interaction technologies of multi-source and multi-mode data perceived from heterogeneous elements Specific to lack of standardized uploading and interoperability of the perceived data, there are the following two problems need to be addressed:

– grammar and semantic mapping rules of multi-mode data for integrating the structured, semi-structured, and unstructured heterogeneous data; and
– devices for multi-source and multi-mode data collection which could provide interfaces and access methods and support a variety of communication protocols.

Integration technologies of multi-source perceived heterogeneous data In production operation processes of physical factories, the complexity of production condition leads to the perceived data becoming with characteristics of multi-dimensionality, coupling, time variability, nonlinearity, etc. Thus, it also brings out some challenges on pre-processing, fusion, and storage of the perceived data, e.g.,

– efficient methods of data cleaning, integration, reduction, and conversion specific for the perceived data;
– dimension reduction method for the massive data and the corresponding clustering and fusion technologies; and
– distributed storage method oriented to smart environment to support information complementation and integrated management which are of characteristics of cross-layer, cross-time, and cross-space.

4.3.2 Technologies for faithful-mirrored virtual models integration

Faith-mirrored modeling technologies for multiple dimensions of production-related elements, behaviors, and rules To ensure the faith-mirrored mapping between production-related virtual models and the complex activities and behaviors in physical factories, there are following three categories of models need to be built:

– for the category of elements, both scalable geometrical models and physical properties models of heterogeneous elements are essential;
– for the category of behaviors, behaviors models and corresponding response models are complementary to depict the functions and influences of some drive and

disturbance in production processes, as well as the ordinal, concurrent, linkage, and other characteristics; and
– as to the category of rules, models of operation rules and evolution laws, and the derived logical models for those rules and laws related to production activities, are also necessary to enrich the digital counterpart of a factory.

Integration and verification technologies of multi-dimension virtual models Considering various granularities and accuracy requirements of above different models, how to evaluate the correlation and compatibility of different categories of models, how to represent the comprehensive digital counterpart of a factory, are the key points to couple and integrate those virtual models. In addition, application reliability of the integrated virtual models should be verified according some indexes, e.g.,

– completeness for elements-related models,
– accuracy for behaviors-related models, and
– rationality for rules-related models, etc.

Real-time interaction and collaborative control technologies for the running of integrated virtual models Based on the specific perception and interconnection devices and the collected data, it aims to achieve both reliable and synchronous operations in the co-simulation processes of the physical factories and their mirrored virtual models. In detail, to ensure the reliability, it depends on the dynamic interaction technologies of virtual models driven by the real-time production activities in factories. As to the other aim of keeping synchronism, it is determined by the events-driven consistency collaborative control modes and strategies, including:

– the registration method between the geometrical models and physical elements,
– the tracking method between the response models and production-related behaviors, and
– the mapping method between the logical models and production-related rules, etc.

4.3.3 Technologies for all of elements/flows/businesses-covered data fusion

Modeling technologies of digital twin data covering all of production-related elements, flows, and businesses Digital twin data is derived and evolved from both physical world and cyber space of factories, so that therein data covering all of elements, flows, and businesses should be uniformly classified at first. Then it should turn to the feature extraction methods specific to each category of the constituents of digital twin data, and finally to establish the unified description models.

Generation mechanisms of multi-source integrated digital twin data Digital twin data provides sufficient data for production operation and management anytime. Thus, its generation mechanisms should cover the following two stages of both initialization and real-time growth.

– For the initialization stage, the integration framework of physical factories, virtual models, and information systems is desired to utilize digital twin data to improve the production operations in factories.
– For the real-time growth stage, the updated modes and dynamic growth rules of digital twin data need to be discussed following the operation processes of factories.

Interaction and iteration-based dynamic evolution theory of digital twin data Different categories of constituents of digital twin data in the continuous closed-loop interaction processes are of the abilities to absorb multi-source data continuously, and to add value through updating, expanding, and enhancing capacity and quality of data. Therefore, the dynamic evolution theory mainly includes:

– the correlation and comparison methods between the categories of real-time data and historical data,
– the correlation and mapping methods between the categories of the perceived physical data and the simulated virtual data, and
– the evolution laws derived by the interaction and iteration between each two categories of data, etc.

4.3.4 Technologies for data-driven and application-oriented services integration

Generation mechanisms of digital twin data-driven services The previous generation and modeling of manufacturing services only consider the data in cyber level. After coming up to integrate physical and cyber levels of data, there appear some new forms and generation mechanisms of services driven by digital twin data. Based on as well as driven by the generation mechanisms of digital twin data, the generation mechanisms of services cover hierarchical expression and closed-loop correction correspondingly, including

– various dominant actions and recessive influences of digital twin data on services; and
– hierarchical models from physical elements, virtual models, and digital twin data, to services, etc.

Integration mode and integrated application mechanisms of services based on dynamic digital twin data The hierarchical models of services reveal both vertical actions and horizontal correlations. First of all, there are coupling and cohesion properties that need to be analyzed preferentially in the hierarchical models. The dynamic evolutionary digital twin data along with the real production operation processes of factories will result in the iterative gains of coupling and cohesion properties among services. Moreover, the potentiation result of coupling and cohesion properties also lead to services integration for their applications, and then bring changes on the application flow.

Integrated services-based control strategies for operation optimization in factories In order to reach smart manufacturing and production management in factories, the typical application demands in operation processes of factories are mainly divided into elements allocation, planning making, process monitoring, and so on. The result of service integration paves a better way to respond to the demands. When built the description models of demands, the iterative and evolutionary digital twin data and their derived integration properties of services both make some differences. Thus, the supply-demand matching mechanisms between digital twin data-driven integrated services and the description models of demands are the core for operation optimizations and control of factories.

5 Conclusions

Cyber-physical integration in current DFs is a key scientific issue that needs to be solved towards smart manufacturing. Some typical problems exist and hinder their operational optimizations. Aiming at improving production operation and management in factories from digital to further smart situation, the main contributions of this paper are concluded and highlighted as follows:

– *Four findings* are summarized after the multi-dimensional analysis on current situation of DFs.
– *A gap of cyber-physical integration* in factories is brought out by comparing the current digital situation with the aims and characteristics of smart manufacturing, and is correspondingly divided into *four sub-aims*, i.e., fully interconnected physical elements integration, faithful-mirrored virtual models integration, all of elements/flows/businesses-covered data fusion, and data-driven and application-oriented services integration .
– *A systematical framework of cyber-physical integration* and its *closed-loop operational mechanisms* for moving factories forward towards smart manufacturing are discussed with consideration of digital twin and manufacturing service, and the *enabling technologies* to implement the indicated four sub-aims step by step are pointed out, respectively.

This work provides a reference for moving current DFs forward towards smart manufacturing. Recently, as the example of upgrading of current DFs towards smart manufacturing, a concept of digital twin shop-floor, especially its cyber-physical integration implementation, as well as its preliminary application, is discussed [48, 49]. It makes sense to test these technologies first under near-industrial conditions and to develop them further in order to ensure their suitability in industrial environments. However, there is still a long way to go for transferring the vision of smart manufacturing into the reality thoroughly based on current situation of DFs.

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