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ORIGINAL ARTICLE

Digital twin-based smart production management and control framework for the complex product assembly shop-floor

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Abstract
Digital twin technology is considered as a key technology to realize cyber-physical systems (CPS). However, due to the complexity of building a digital equivalent in virtual space to its physical counterpart, very little progress has been achieved in digital twin application, especially in the complex product assembly shop-floor. In this paper, we propose a framework of digital twin-based smart production management and control approach for complex product assembly shop-floors. Four core techniques embodied in the framework are illustrated in detail as follows: (1) real-time acquisition, organization, and management of the physical assembly shop-floor data, (2) construction of the assembly shop-floor digital twin, (3) digital twin and big data-driven prediction of the assembly shop-floor, and (4) digital twin-based assembly shop-floor production management and control service. To elaborate how to apply the proposed approach to reality, we present detailed implementation process of the proposed digital twin-based smart production management and control approach in a satellite assembly shop-floor scenario. Meanwhile, the future work to completely fulfill digital twin-based smart production management and control concept for complex product assembly shop-floors are discussed.

Keywords Digital twin · Smart manufacturing · Production management and control · Big data · Complex product · Assembly shop-floor

1 Introduction

Shop-floor is a convergence point with information flow, material flow, and control flow. To date, the question of how to achieve high production efficiency, low production cost, and high product quality in the shop-floor with the appropriate management and control methods has attracted wide attention. Before the 1960s, shop-floor production management and control were fulfilled mainly by hand. In this period, a series of well-known events marked its development. For example, in 1776, the British economist Adam Smith stressed the importance of the labor division in his book "Wealth of Nations." In 1911, Taylor, known as the "father of scientific management," advocated that management was a kind of science. At that time, many enterprises applied a pyramid-style organizational structure method to achieve the production target. In 1913, the Ford Motor Company established a T-car assembly line and initiated the era of mass production. In the early 1960s, shop-floor production management and control stepped into a computer-aided era with the wide use of computer applications. Afterwards, the shop-floor production management and control approach evolved from single point management to integrated management, collaborative management, and smart/intelligent management, as is shown in Fig. 1.

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Single-point production management and control stage using single functional systems (from the 1960s to the early 1990s) In this period, many shop-floor production management and control systems for a single function or a single field were proposed, such as production scheduling systems [1], data acquisition systems, quality management systems, and material management systems. The main feature of this stage is that computers gradually became the main technical tools to carry out shop scheduling, data acquisition, material management, quality management, etc. Most of them aimed at achieving productivity gains by increasing production efficiency or reducing production cost. Although quite a few enterprise

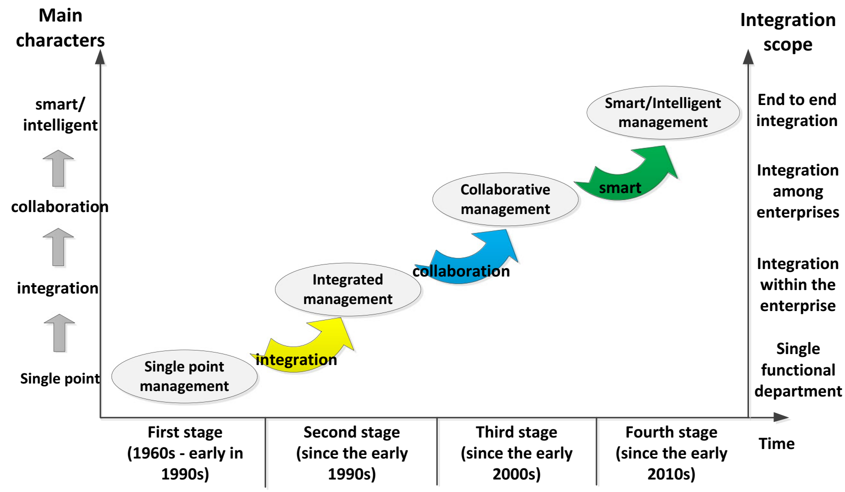

Fig. 1 Development of shop-floor production management and control approach

information systems emerged in this period, such as MRP/MRPII [2], Enterprise Resource Management (ERP), and Product Data Management (PDM), shop-floor activities did not catch much attention by information system specialists [3].

Integrated production management and control stage based on MES (since the early 1990s) In the early 1990s, the manufacturing execution system (MES), as a specific application system at the shop-level, was developed [4]. MES consists of most functions of production management and control, such as production planning and scheduling, material delivery and control, product quality management and control, production cost control, and equipment management and maintenance. MES aims to realize integrated production management and control in the shop-floor [5].

Collaborative production management and control stage using networking manufacturing technologies (since the early 2000s) With the rapid development of networking manufacturing technologies in the early 2000s, many advanced manufacturing strategies and paradigms emerged, such as agile manufacturing [6], collaborative manufacturing [7], e-manufacturing [8], supply chain management [9], and e-commerce [10]. These strategies and paradigms accelerated the integration and collaboration among the supply chain enterprises in the product manufacturing and assembly process. Enterprise competitiveness and production efficiency were significantly improved in this stage.

Smart/intelligent production management and control stage based on smart/intelligent manufacturing technologies (since the early 2010s) The concept of smart/intelligent manufacturing was born in the 1980s but attracted wide attention in this period. In 2011, the Smart Manufacturing Leadership Coalition (SMLC) was founded in the USA, and then the concept of Industrial Internet was proposed along with an action plan for Smart Manufacturing [11]. In 2013, the German Federal Ministry of Education and the Federal Ministry of Economy and Technology put forward a whole new concept of "Industrial 4.0." It sought to bring the manufacturing industry into the smart/intelligent phase through the full use of cyber-physical systems (CPS). In 2015, the Chinese government issued an ambitious plan called, "Made in China 2025." It aims to realize intelligent manufacturing in a new round of scientific and technology revolution.

Nowadays, shop-floor production management and control stepped into its second stage. However, due to the rapid development of new-generation information and communication technologies, such as Internet of things (IoT), cloud computing, big data, mobile Internet, and artificial intelligence (AI), ways of implementing shop-floor production management and control are undergoing a significant change. Meanwhile, the integration scope is also gradually shifting from interior to exterior, aiming to fulfill collaborative production management and control among the supply chain enterprises. Moreover, methods of shop-floor production management and control are continuously evolving from automation and digitalization to networking and collaboration and, ultimately, to the smart/intellectualization. Thus, from the perspective of evolving process, the question of how to realize smart production management and control in the shop-floor is imperative. Additionally, it is a common issue for most advanced manufacturing strategies and paradigms [12] (such as smart manufacturing, industrial Internet, Industrial 4.0, Made in China 2025, wireless manufacturing [13], cloud manufacturing [14, 15], wisdom manufacturing [16]). Smart production management and control in the shop-floor have become one of the most popular issues for domestic and foreign scholars and companies.

A complex product refers to a product that is complex in terms of customer demand, product composition, product technology, manufacturing process, and project management, such as missile, satellite, rocket, and aircraft. Assembly is the last production step and one of the most important processes, since the quality, life, performance, reliability, and maintainability of a product mostly depend on assembly results. Recently, to improve assembly efficiency, reduce production cost, and ensure product quality, most aviation and aerospace enterprises that produce complex products have already taken actions to implement smart production management and control in their assembly shop-floors. Therefore, as an example to analyze the current dilemmas in complex product assembly shop-floor, we use satellite assembly. And a digital twin-based framework for a satellite assembly shop-floor was proposed to fulfill smart production management and control.

The remainder of the paper is organized as follows: Sect. 2 analyzes the existing problems in satellite assembly shop-floors. Sect. 3 investigates the development and application of digital twin technique. Based on digital twin, Sect. 4 presents a framework of smart production management and control for a satellite assembly shop-floor. To fulfill the framework, Sect. 5 presents four key technologies in detail. Sect. 6 illustrates the implementation process of applying the proposed framework in a satellite assembly shop-floor. The last part concludes the main contributions of the paper and discusses research issues in the future.

2 The existing problems in satellite assembly shop-floors

In 2017, Yao [17] proposed a new manufacturing paradigm, called "proactive manufacturing," according to the utilization degree and exploration depth of data, and pointed out that the manufacturing paradigm would evolve from "traditional" passive manufacturing (also known as reactive manufacturing) to real-time manufacturing and predictive manufacturing and, ultimately, to proactive manufacturing. Similarly, the production management and control strategies in the assembly shop-floor will also go through these four stages: passive (reactive), real-time, predictive, and proactive. The evolution of shop-floor production management and control strategies is shown in Fig. 2.

The first stage: passive (reactive) management and control method In this stage, most data are collected via paperwork or offline manual input. The amount of data is not large, and the traditional relational databases can meet most of the requirements for data storage, organization and management. As the data is not real time, data processing and analysis is always delayed. Shop-floor production management and control is normally based on historical data.

The second stage: real-time management and control method In this period, with the in-depth application of IoT technology in the industrial field, assembly enterprises can achieve smart perception of manufacturing resources and online collection of real-time data by means of radio frequency identification (RFID) tags and readers, smart sensors, bar codes, wireless networks, sensor networks, Ethernet, etc. In this stage, the data is real time. Compared with a passive strategy, the real-time strategy has a higher level of demand for the timeliness of data collection, processing, analysis, and decision-making.

The third stage: predictive management and control method In this stage, along with wide applications of machine learning, neural networks, data mining, cloud computing, and other big data-related technologies, it is possible to predict potential shop-floor production disturbance, the quality of a product, the behavior and status of equipment and human, etc. The relevant personnel can prevent potential disturbances, anomalies, and problems in advance following the prediction results. The predictive strategy can dig out the foresight value of data by means of big data and digital twin technology. Compared with a real-time strategy, a predictive strategy comes along with more uncertainties due to the unknown future.

The fourth stage: proactive management and control method During this stage, the manufacturing system can not only predict the behavior and status of equipment and human resources, but also make decisions autonomously based on prediction results. It can even drive and control physical entities in the real space based on CPS' self-adaptive and self-reconfiguration functions. Proactive strategy is a natural extension of predictive strategy combined with AI and digital twin technology. Applying big data, proactive method is the ultimate goal of smart production management and control.

Currently, most assembly companies are still in the first stage. Unfortunately, there are still some companies which have not yet achieved electronic data acquisition in assembly shop-floors. Moreover, no assembly enterprise reports that it has realized predictive management and control in assembly shop-floors. Therefore, how to implement predictive management and control in assembly shop-floors is one of the critical issues for assembly enterprises. Only on this basis can assembly companies go forward into proactive management and control stage and eventually achieve smart management and control. Likewise, for satellite assembly enterprises, it is imperative to implement predictive production management and control in assembly shop-floors.

Generally, the assembly process of a satellite has the following characteristics: manual-based discrete assembly, single or small batch production, strict quality control, and long production cycle. For each satellite, the related product data must

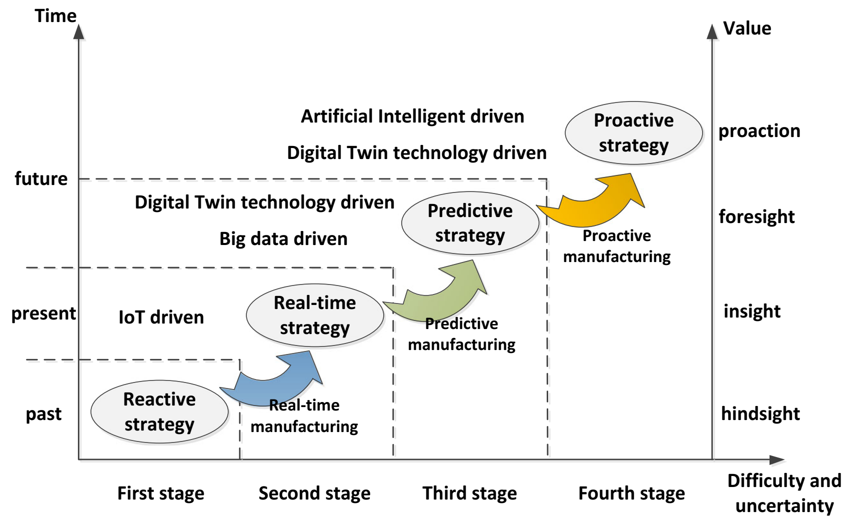

Fig. 2 The evolution of shop-floor production management and control strategies [17]

be well collected, organized, and managed, so that the entire production process can be monitored and traced if required. However, due to the uncertainty, complexity and dynamic characteristics of the assembly shop-floor and product itself, disturbances emerged frequently in satellite assembly shop-floors. Under the circumstances, prompt response to the disturbance or disturbance prediction is a critical issue for satellite assembly enterprises before the realization of smart shop-floor production management and control.

As for the above problem, digital twin technology is considered as a feasible and effective approach [18]. Digital twin technology refers to the process or method of describing and modeling a physical entity's characteristics, behavior, and performance by means of digital technology. It embodies an effective approach to realize the interaction and convergence between the cyber and physical worlds. Digital twin technology is considered as a key technology to realize CPS (the core to achieve smart manufacturing), since the main function of CPS is to realize the association mapping, interaction and convergence between cyber and physical spaces. Digital twin technology applies not only mankind knowledge to establish a virtual model, but also virtual model simulation technology to explore and predict the unknown world. It can search a better way to continually stimulate human's initiative thinking and pursue optimal progress. Meanwhile, a digital twin can act as a single source to organize and manage shop-floor data based on virtual models. Thus, digital twin technology provides new concepts and tools for current manufacturing innovation and development. It is a novel and promising approach towards predictive production management and control in shop-floors.

3 Overview of digital twin

The introduction of the concept of "twin" in the field of manufacturing can date back to NASA's Apollo project in the late 1960s. In this project, NASA created two identical space vehicles. The one that was left on Earth was called "the twin," which was used to mirror the condition of the space vehicle that performed the mission. From this point of view, the twin was referred to as a prototype that mirrored the real operating condition for the simulation of real-time behavior [19]. It should be noted that the twin was a physical entity at that time.

In 2003, Grieves introduced the concept of "a virtual, digital representation equivalent to a physical product" or a "digital twin" at the University of Michigan's Product Lifecycle Management course and presented its conceptual model [20]. The conceptual model stemmed from the expectation that all the data and information of a physical entity could be put together for a higher level of analysis. Although this model was then not regarded as the digital twin (it was referred to as the mirrored spaced model in 2003–2005 [21] and information mirroring model in 2006–2010 [22]), it embodied all functions of a digital twin. It consisted of three critical parts for a digital twin, i.e., the physical space, the virtual space, and the linkage or interface between the two spaces. Grieves' concept was treated as the origin of digital twin. In 2011, in the book "Virtually perfect: driving innovative and lean products through product lifecycle management" [23], Grieves quoted his co-author Vickers's way of describing this model—digital twin—and this comes to be in use today [24].

In 2012, NASA and the US Air Force (USAF) Research Laboratory presented a digital twin paradigm for future vehicles, which met the requirements of lighter mass, higher loads, and longer service in more severe conditions. The digital twin was defined as an integrated multi-physics, multi-scale, probabilistic simulation of an as-built vehicle or system, which incorporated the best available physical models, updated sensors data, and historical data to mirror the life and condition of the corresponding flying twin [25]. In the same year, NASA [26] released a road map called "Modeling, simulation, information technology, and processing," and then the term digital twin was widely applied for product or shop-floor.

In summary, digital twin is a virtual, dynamic model in the virtual world that is fully consistent with its corresponding physical entity in the real world and can simulate its physical counterpart's characteristics, behavior, life, and performance in a timely fashion. Such a concept is also known as digital twin model in Germany.

Currently, digital twin-related methodology and technology have been attempted in industrial fields, and showed great potential. For example, in 2011, Tuegel et al. [27] sought to establish an ultra-high fidelity simulation model, the digital twin, for each space vehicle with an independent tail number to accurately predict the life and damage of a spacecraft structure. In 2012, the concept of "airframe digital twin" was proposed aiming to reduce the maintenance cost of the airframe [28]. In 2013, Reifsnider et al. [29] adopted a new technique of dielectric spectroscopy to support a multi-disciplinary physics-based methodology. Such technique built a solid foundation for an ultra-high fidelity simulation to digitally mirror the feature of the corresponding flying physical twin. In 2014, Cerrone et al. [30] implemented an accurate prediction of the crack path for each specimen using its as-manufactured geometry, which gave a better definition of digital twin through a more intuitive example. In 2015, General Electric (GE) [31] sought to realize real-time monitoring, timely inspection, and predictive maintenance of engines based on digital twin technology. In 2016, Boschert and Rosen [32] studied the application methods of digital twin in the simulation of complex systems. And digital twin was regarded as the next wave of modeling and simulation. DebRoy et al. [33] proposed a method to construct the first-generation digital twins of 3D printing machines. Schroeder et al. [34] proposed a conceptual framework of digital twin based on a web service. In 2017, in a NASA-related system, Grieves [24] studied methods of fault prediction and elimination for such a system based on digital twin technology and then applied and tested it. Tao et al. [35] proposed a new method for product design, manufacturing, and service driven by digital twin. Furthermore, three cases were illustrated for the future applications of digital twin in three phases of a product.

According to the rough annals of digital twin listed above, it is obvious that the efforts have mainly focused on the field of product management. However, in most recent past, some scholars began to apply digital twin technology to the shop-floor or production system. Stark et al. [36] adopted digital twin as a testing method in a new approach for next generation manufacturing systems. Tao et al. [12, 37] proposed a digital twin shop-floor to realize the interaction and convergence between physical and virtual spaces.

4 Framework of digital twin-based smart production management and control for a satellite assembly shop-floor

Based on the analysis above, we propose a framework of digital twin-based smart production management and control for a satellite assembly shop-floor, as shown in Fig. 3.

Physical assembly shop-floor and assembly shop-floor digital twin The physical assembly shop-floor is the collection of existing physical entities. The assembly shop-floor digital twin in virtual space is the reconstruction and digital mapping of the physical assembly shop-floor. They exchange data/information/knowledge through the assembly shop-floor big data storage and management platform. By constructing an assembly shop-floor digital twin, the working progress and working status of assembly stations, products, and manufacturing resources in the physical assembly shop-floor can be dynamically, realistically, and accurately mapped in the virtual space. Therefore, the relevant personnel can monitor and track the operating condition of the physical assembly shop-floor any time. In addition, various types of shop-floor production activities (such as shop scheduling, production logistics planning, manufacturing resources allocation) and production processes in the physical assembly shop-floor can be simulated, evaluated, validated, and verified through the assembly shop-floor digital twin in the virtual space. This provides an effective tool to choose and conduct an optimal production strategy based on digital twin simulation results.

Assembly shop-floor big data storage and management platform In recent years, large amounts of real-time data (e.g., environmental awareness data, machine operation data, sensor data) and unstructured multi-media data (e.g., video, audio, photos) in the assembly shop-floor abound. The assembly shop-floor data presents the typical "3V" characteristics of big data [38], i.e., volume (large amount of data), variety (various types and forms of data), and velocity (high data generation speed). In a satellite assembly shop-floor, due to frequent production disturbances, the shop-floor data also shows characteristics of uncertainty, high noise, and variability. It is necessary to establish a big data storage and management platform for the assembly shop-floor, which forms a solid basis for digital twin. The construction of a shop-floor assembly digital twin means that the assembly shop-floor big data not only include data concerning the physical shop-floor, but also include data related to the shop-floor in cyber space. The latter consists of model data and operation data of the digital twin, e.g., simulation data, prediction data, and assessment data. The big data storage and

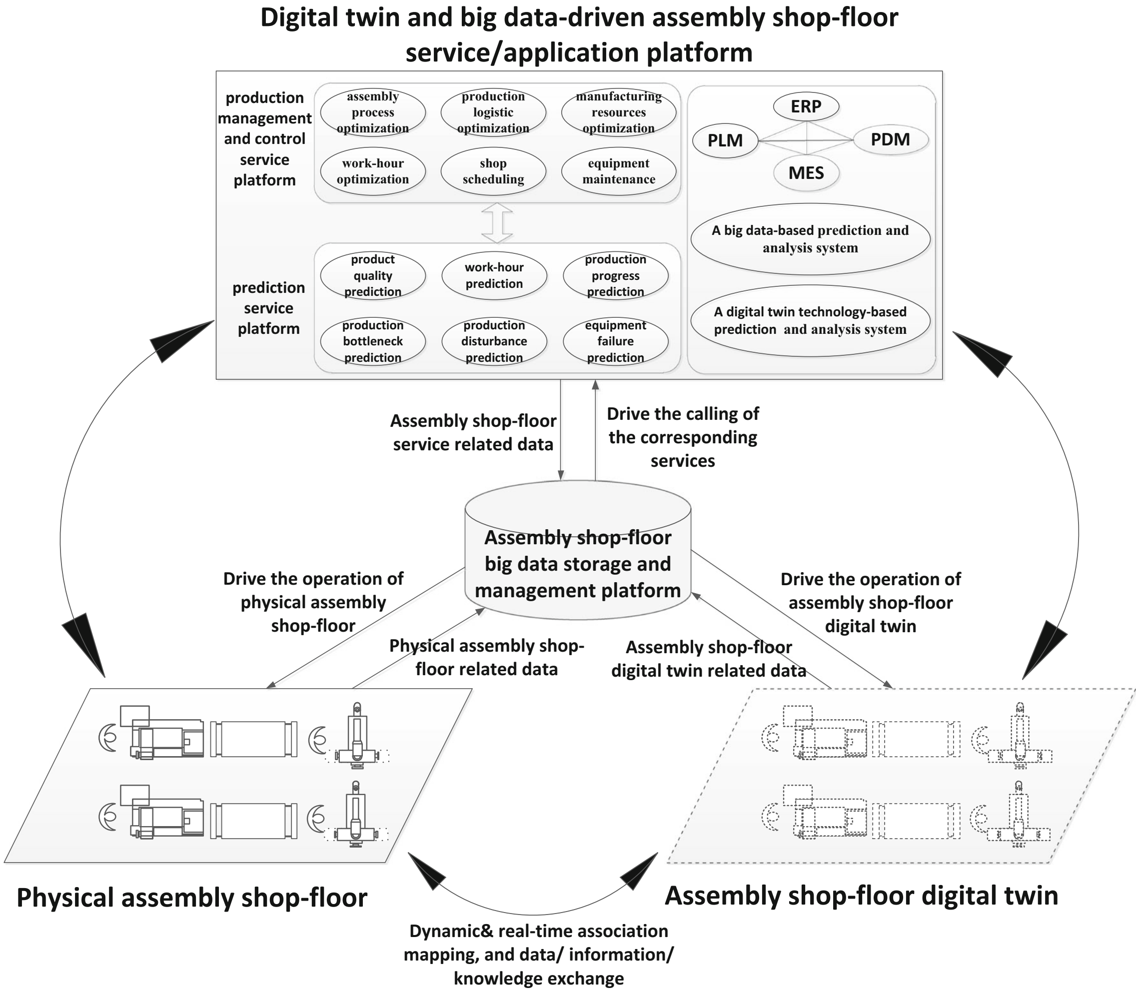

Fig. 3 Framework of digital-twin based smart production management and control for a satellite assembly shop-floor

management platform acts as a single data source and provides data support for the physical assembly shop-floor, the assembly shop-floor digital twin, and the shop-floor service/application platform. It is the driving force and foundation in a smart production management and control system.

Digital twin and big data-driven assembly shop-floor service/ application platform Assembly shop-floor service/ application refers to the collection of technologies that support the functional and target requirements of smart production management and control. It includes monitoring, prediction, and optimization control of manufacturing resources, production activities, and production processes. A digital twin and big data-driven assembly shop-floor service/application platform provide real-time and predictive production management and control services for the physical assembly shop-floor. It is composed of a prediction service platform and a production management and control service platform. The prediction service platform incorporates functions of product quality prediction, work-hour prediction, production progress prediction, production bottleneck prediction, production disturbance prediction, equipment failure prediction, equipment life prediction, material requirement prediction, etc. The production management and control service platform comprises assembly process optimization, production logistic optimization, manufacturing resources optimization, work-hour optimization, shop scheduling, equipment maintenance, etc. The systems that support the service/ application platform are enterprise information systems (e.g., MES, PLM, ERP, PDM), a big data-based prediction and analysis system, and a digital twin technology-based prediction and analysis system. The prediction service platform is the premise of predictive management and control, which provides foresight information for the production management and control service platform. On this basis, the production management and control service platform can realize dynamic, real-time, or predictive optimized management and control of manufacturing resources, production activities, and production processes in the satellite assembly shop-floor.

5 Key technologies

Based on the proposed framework, this paper illustrates in detail four key technologies. They are as follows: (1) real-time acquisition, organization, and management of the physical assembly shop-floor data, (2) construction of the assembly shop-floor digital twin, (3) digital twin and big data-driven prediction of the assembly shop-floor, and (4) digital twin-based assembly shop-floor production management and control service.

5.1 Real-time acquisition, organization, and management of the physical assembly shop-floor data

As mentioned in Sect. 2, an efficient method to collect, organize, and manage numerous assembly shop-floor data is one of the main issues that impeding a satellite assembly shop-floor in its entry to smart. We adopt a workflow technology-based approach to realize data acquisition, organization, and management in a satellite assembly shop-floor [39, 40]. This approach can effectively organize and manage assembly shop-floor data. It promotes the shop-floor paperless production and lays a solid foundation for the smart development of the satellite assembly shop-floor.

With the advances of sensor network, wireless network, automation technology, semantic identification, and analysis technology, a wide range of applications have been achieved in manufacturing/assembly shop-floors with RFID as a representative IoT technology. This meets the needs of manufacturing/assembly shop-floors in real-time information acquisition [41], material delivery [42], work-in-progress (WIP) management [43, 44], product quality monitoring [45], manufacturing cost tracking [46], adaptive production process control [47], etc. Therefore, IoT technology can be applied in a satellite assembly shop-floor to ensure the timeliness of shop-floor data.

Additionally, the digital twin concept provides a new solution to data management. In the case of a product, the product digital twin acts as a single data source throughout the product lifecycle. It enables vendors to collaborate in the process of product design, process planning, product assembly, product use and maintenance, etc. In the satellite assembly shop-floor, it is possible to achieve visualized and integrated management of shop-floor data based on digital twin.

Below is a framework we propose for real-time acquisition, organization and management of physical assembly shop-floor data. It is realized by means of IoT, workflow, and digital twin technologies, as shown in Fig. 4.

Smart access to manufacturing resources in the physical assembly shop-floor Smart access to manufacturing resources is the premise of real-time perception. Real-time perception forms the basis of real-time data acquisition, which is the foundation of real-time management and control. A manufacturing resource that is equipped with sensing devices (with perceptual or perceived ability) not only helps to achieve its own business logic, but also enables interactive and collaborative work with other manufacturing resources [41]. At the same time, place-fixed RFID readers or handheld RFID readers at the entrance and exit of the warehouse, assembly station, WIP buffer area, and other control areas can sense RFID tags automatically in a timely fashion within the perception scope. They retrieve the corresponding data to achieve real-time perception and status updating of manufacturing resources.

Real-time acquisition of physical assembly shop-floor data The data collected in the physical assembly shop-floor are divided into three categories: real-time perception data, production process data, and production activity plan data. Real-time perception data includes personnel status data, production logistics status data, equipment operation data, etc. Production process data refer to the data related to product assembly process, including assembly progress data, completion data, work-hour data, product quality data, implemented material data, assembly station status data, etc. Production activity plan data comprises the data concerning the production activity plan data, such as assembly plan data and material distribution plan data.

In the production process, a series of events, such as material flow, personnel flow, equipment operation, process completion, and product inspection are main events. Firstly, these events may trigger real-time perception of manufacturing resources and generate real-time perception data regarding the manufacturing resources. For example, when a material is out of a warehouse, the RFID reader in the warehouse exit perceives the RFID tag of the material and obtains the material-related information. Then, the middleware software estimates the location of the material according to the location of the reader. After that, the relevant data are transmitted to the database. In addition, these events might trigger the collection action of production process data. Secondly, real-time perception data and production process data will drive shop-floor managers to dynamically optimize the production activity plans. In this circumstance, production activity plan-related data are generated. Finally, the newly developed shop-floor production activity plan is fed back to the physical assembly shop-floor and guides the production second round. Thus, a series of events might occur and form a closed-loop data acquisition stream in the physical assembly shop-floor.

Assembly shop-floor data organization and management Product bill of materials (BOM) is the data source of material requirements in the assembly shop-floor, which

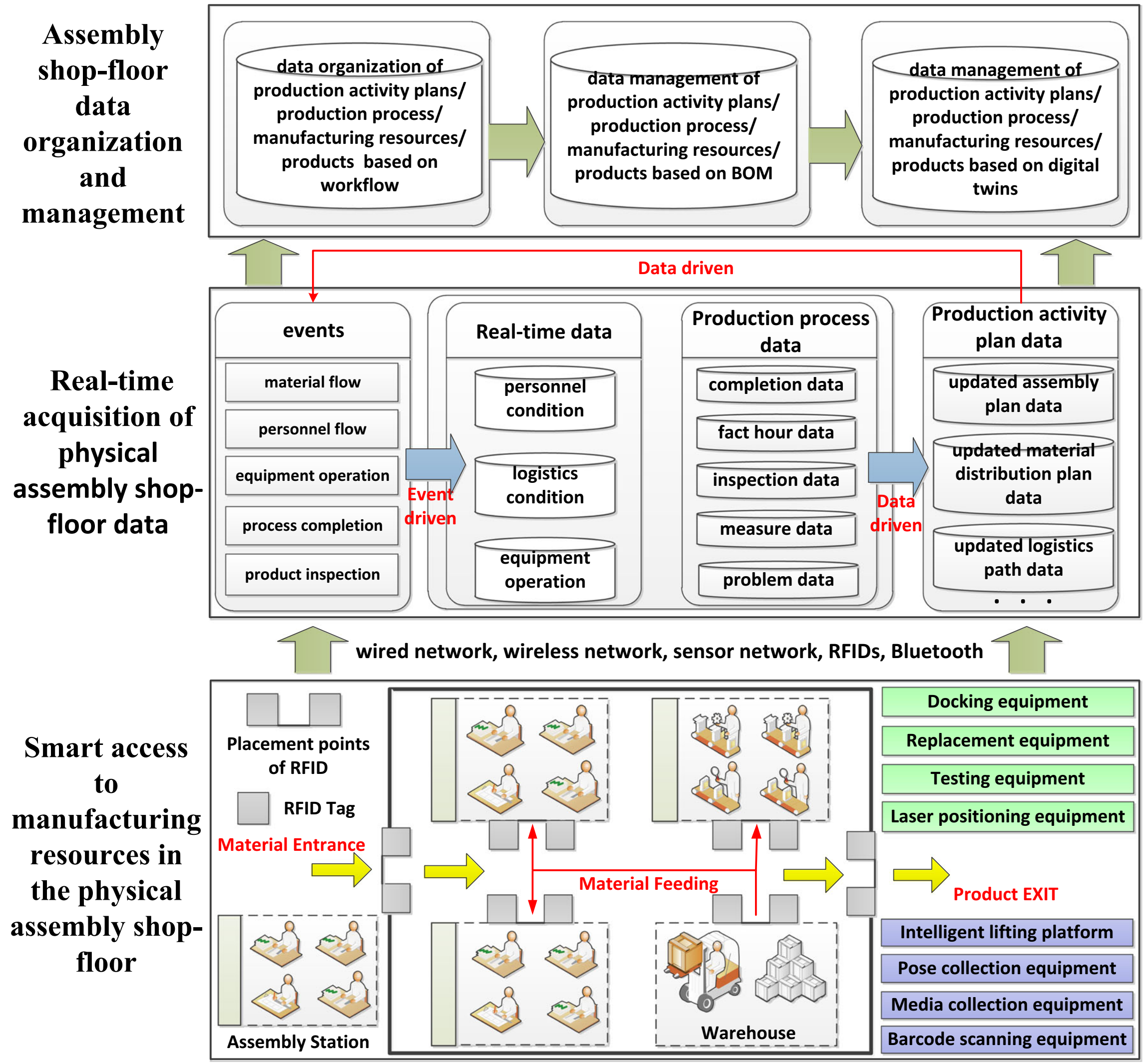

Fig. 4 Framework for real-time acquisition, organization, and management of physical assembly shop-floor data

passes through stages of product design, process planning, and product assembly. Assembly shop-floor data can be managed based on product BOM and digital twins. The detailed approach is listed as follows. (a) In the product design stage, the designer builds the product 3D model and develops the product BOM. In the assembly process planning stage, the technician draws the assembly process flowchart (formed by process flow nodes with serial and parallel connection) for the node of product or assembly/component on the BOM. The process/step content information, inspection information, and material information are structurally related to the process flow nodes. (b) In the production scheduling stage, the dispatcher firstly receives the assembly production plan issued by the ERP system. The assembly plan has not only already been associated with the product node or assembly/component node on the product BOM, but also structurally related to the assembly process flowchart. On this basis, the assembly plan is broken down into various assembly tasks, and the assembly process flowchart is automatically combined with each assembly task. (c) To further refine the scheduling, the assembly task is decomposed into a daily plan. The daily plan is structurally associated with one or more process flow nodes. By this way, the process/step content information, inspection information, and material information can be structurally associated with an assembly process flow node, a daily plan, an assembly task, and an assembly plan. Therefore, the data related to production activity plans/production process/manufacturing resources/products can be well organized and managed based on product BOM. On this basis, through the construction of digital twins (e.g., product digital twin, assembly shop-floor digital twin) and the mapping relationship between BOM and digital twins, the integrated management of assembly shop-floor data can be realized.

5.2 Construction of the assembly shop-floor digital twin

To implement the proposed framework, the first task is to build an assembly shop-floor digital twin in the virtual space to map the physical assembly shop-floor using digital modeling technology. The digital twin can be built considering the following three levels: element, behavior, and rule. At the element level, the assembly shop-floor digital twin is composed of shop-floor production elements' geometric models and physical models, including shop-floor model, production line models, assembly station models, manufacturing resource models (assembly/inspection/measurement/testing/logistics equipment models, personnel models, material models), product models, and environment models. At this level, the commonly applied tools that constructing 3D geometric models are Pro/E, CATIA, SolidWorks, AutoCAD, etc. Methods like finite element method (FEM) and boundary element method (BEM) can be used to simulate the physical functions and performance of the elements. At the level of behavior, the assembly shop-floor digital twin is composed of elements' behaviors and responsive mechanisms, including the virtualized models of the personnel's actions, equipment's operations, and materials' transportations. The most commonly used tools are FlexSim, Unity3D, 3DVIA Composer, etc. At the rule level, the assembly shop-floor digital twin consists of association rule models among elements, shop-floor operation rule models, and evolution rule models, which ensure that the operating mechanism of shop-floor digital twin can match real situations and truly simulate the physical shop-floor's behavior, status, operation, and evolution. Only with the use of these components can the shop-floor digital twin truly achieve its functions of evaluating, predicting, validating, and optimizing the production of the physical shop-floor. To build these rule models, data analysis algorithms, data mining algorithms and knowledge mining algorithms are basic necessities.

To ensure the effectiveness and high fidelity of a digital twin, there are some key issues needed to be studied: (1) Methods to connect and fuse all the shop-floor models. This is a premise of building a shop-floor digital twin. Methods such as complex network and multi-agent can be applied to tackle this issue. (2) Methods to validate and test the accuracy of models. Tao et al. [37] proposed a Verification Validation and Accreditation (VV&A)-based method to solve the problem. However, some detailed implementation technologies still need to be studied in the future. (3) The mechanism, methods, and technologies of operating and evolving models. Tao et al. [37] provided a feasible models operation and evolution mechanism that can be used as a guideline for the future work. The methods and technologies that are involved in the mechanism are still in its infancy. (4) Methods to implement the interaction and interconnection between shop-floor data and shop-floor models. It is the basis of applying a shop-floor digital twin, since a digital twin is a dynamic model that is in coherence with its physical counterpart. For example, when a component has been installed on a product, the workers will collect completion data and implemented material data. Thenceforth, driven by the collected data, the corresponding 3D model should transform from empty to solid in a timely fashion so that the digital twin can intuitively reflect the real condition in the physical space.

5.3 Digital twin and big data-driven prediction of the assembly shop-floor

At present, predictive manufacturing is mainly applied at the product use and service stage, including fault diagnosis and prediction, predictive maintenance and repair, and equipment health management and life prediction. However, it is rarely involved in the product assembly stage. It is an urgent demand to realize predictive management and control in the assembly shop-floor for assembly enterprise. In comparison with traditional "small" data analytical tools, big data application has the following characteristics: (1) From passive processing to active prediction. With big data, it is possible and feasible to predict incoming disturbances at the beginning of production process. The workers can take actions proactively to prevent or resolve the possible disturbances in advance. (2) From causality analysis to relevance analysis. With big data, the analytical model for optimization and decision-making is transformed from a causal relationship analysis model to a correlation analysis model. This provides a new approach for product/process optimization and decision-making, especially for large-scale resource combination and optimization problems. Moreover, as mentioned above, digital twin technology not only takes advantage of mankind knowledge to establish a virtual model, but also utilizes virtual model simulation technology to explore and predict the unknown world. It provides new concepts and tools for current manufacturing innovation and progress. It is a novel way to explore and predict the future.

Below we propose a prediction framework for the satellite assembly shop-floor, in combination with digital twin and big data, as shown in Fig. 5.

Big data-driven prediction process For a specific prediction requirement, big data-based prediction service platform calls the corresponding prediction model that is encapsulated in the service platform. The input consists of historical data, experiences, knowledge, and the real-time data collected in the physical assembly shop-floor. The output is theoretical prediction values/results.

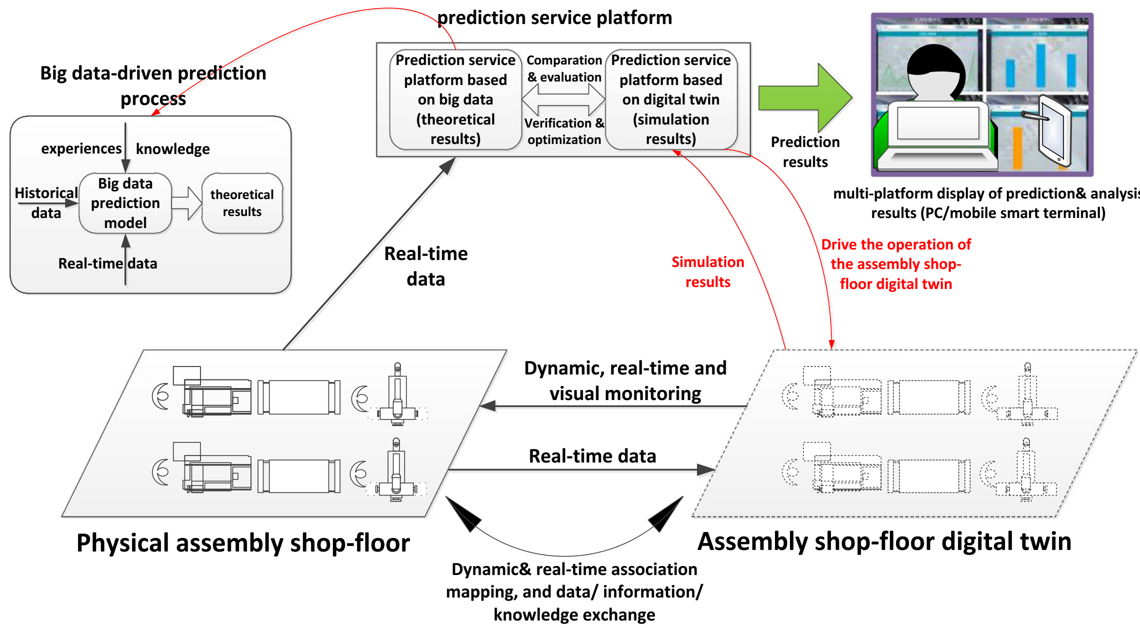

Fig. 5 Digital twin and big data-driven prediction framework for the satellite assembly shop-floor

Digital twin-driven prediction process First, real-time data collected in the physical assembly shop-floor should be associated with the assembly shop-floor digital twin. In this case, the shop-floor managers can visually and dynamically track and monitor the operation condition of the physical shop-floor through the shop-floor digital twin. Then, the digital twin-based prediction service platform drives the assembly shop-floor digital twin to simulate the future's production operation of the physical assembly shop-floor. Finally, the simulation results generated by the shop-floor digital twin will feed back to the service platform.

Comparison, analysis and optimization of prediction results The theoretical analysis results, based on big data, are compared with the simulation findings based on digital twin technology. It can not only achieve an effective accuracy evaluation for prediction results, but also maintain improvement of the big data prediction models and digital twin models to achieve more accurate prediction.

5.4 Digital twin-based production management and control service

Based on digital twin technology, Fig. 6 depicts a production management and control service framework for the satellite assembly shop-floor.

Map between the real-time data collected in the physical assembly shop-floor and the corresponding model in the assembly shop-floor digital twin It makes certain that the assembly shop-floor digital twin in the virtual space can truly reflect and mirror the operation condition of the physical assembly shop-floor. The condition can be reflected by the working status and working progress of manufacturing resources (personnel, equipment, and materials), products, assembly stations, and production processes.

Real-time decision-making based on the dynamic data collected in the physical assembly shop-floor The application scenarios include temporary assembly tasks added, product lead time changed, equipment shutdown or failure, product quality problems found, product design and process changed, and other kinds of production disturbances. Moreover, with the prediction results obtaining from the prediction service platform, the production management and control service platform can carry out predictive decision-making.

Initial control scheme simulation in the assembly shop-floor digital twin The simulation results can be utilized to evaluate the feasibility and effectiveness of the scheme. Repeating this closed-loop process in a reasonable time range can result in the most optimal production control scheme. It is our aim to apply those findings to guide the production of the physical assembly shop-floor.

6 A case study

Figure 7 depicts the implementation process for digital twin-based smart production management and control in a satellite

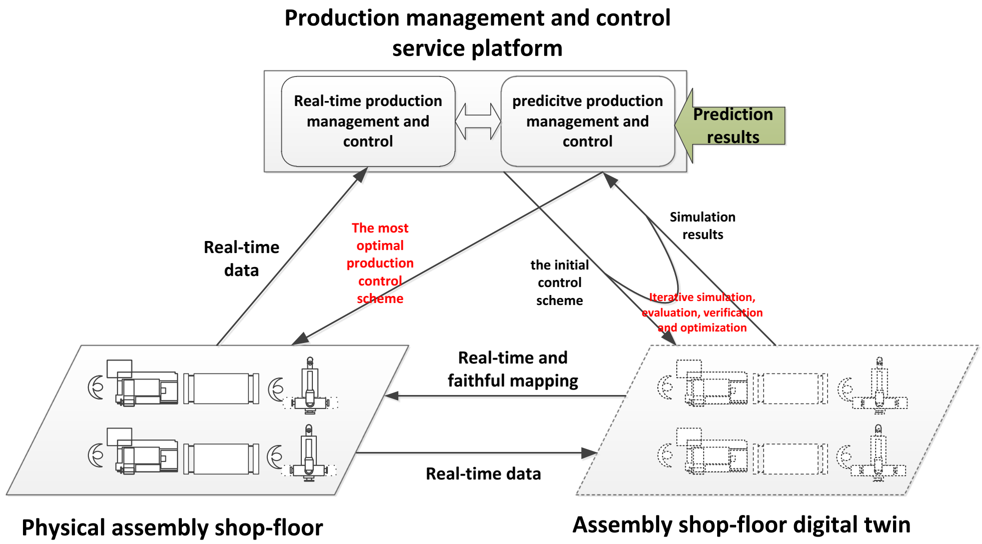

Fig. 6 Digital twin-based production management and control service framework for the satellite assembly shop-floor

assembly shop-floor. The process consists of two main phases: the construction phase and the operation phase.

6.1 Construction phase

The construction phase contains two parts, i.e., the construction of shop-floor IoT networks and the construction of a shop-floor digital twin.

6.1.1 Construction of shop-floor IoT networks

According to the requirements of production control and data acquisition in the satellite assembly shop-floor, shop-floor IoT networks should be constructed to realize the real-time perception and data acquisition. It enables real-time and dynamic monitoring and tracking of manufacturing resources. The concrete realization method can draw in the references [48, 49], which includes, primarily two steps: (1) Identify manufacturing resources uniquely using RFID tags and bar codes, so that manufacturing resources can be perceived. (2) Build an industrial LAN, wireless and mobile networks, Bluetooth, and RFID sensor networks in the shop-floor to implement smart perception of manufacturing resources and transmission of real-time data. Real-time data normally need to be pre-processed in the middleware software to produce available information for enterprise information management systems (e.g., MES) processing and utilizing.

6.1.2 Construction of a shop-floor digital twin

The details on how to build a shop-floor digital twin are described in Sect. 5.2. The sketch interfaces of constructing a digital twin for a satellite assembly shop-floor are shown in Fig. 8.

6.2 Operation phase

6.2.1 Real-time acquisition and organization of the assembly shop-floor data

The data collected in a satellite assembly shop-floor consists of three categories: (1) Real-time perception data of manufacturing resources, collected by RFID, sensors, and other sensing technologies. It includes personnel status data, equipment operation data and production logistical data. (2) Production process data collected by human-computer interactions. It includes the completion data (can be used for assembly progress statistics), work-hour data, product quality data, implemented material data, and reverse problem data. (3) Production activity plan data (including the initial plan data and updated plan data) generated by the as-built intelligent optimization algorithms or manual fine-tuning. The interfaces of collecting and organizing a satellite assembly shop-floor data are shown in Fig. 9.

6.2.2 Operation of the satellite assembly shop-floor digital twin

This step consists of two levels: The first one is to mirror the working status and working progress of the physical satellite assembly shop-floor dynamically, visually, and accurately in a timely fashion. For example, before assembling a satellite, we can set its 3D model as empty. When a worker assembles a structure board, the corresponding structure board model becomes solid automatically. If the structure board is with a quality defect, the color of the corresponding model becomes yellow. So we can mirror the assembly progress and status of this satellite in a timely fashion. Moreover, it also records the entire operation processes of the physical assembly shop-floor to ensure data traceability. The other one is to predict the

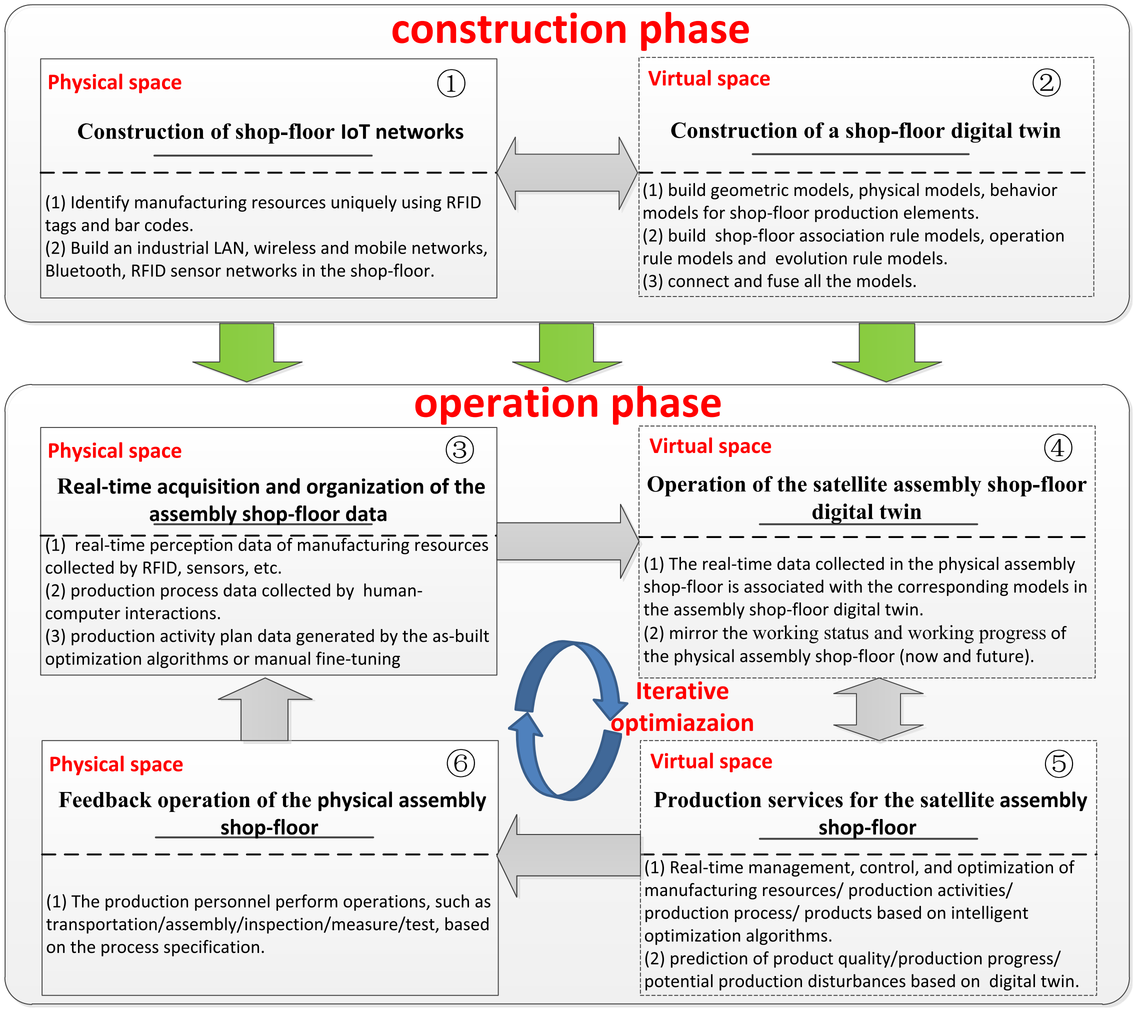

Fig. 7 Implementation process for digital twin-based smart production management and control in a satellite assembly shop-floor

future working status and working progress of the physical assembly shop-floor. For example, when a worker completes the first procedure, the completion data, fact hour data, implemented material data, measure data, etc., are available to collect. If the operator noticed that the second procedure is a key procedure, he or she may call the service platform to run the shop-floor digital twin to discover if some anomalies occur in operating the second procedure.

6.2.3 Production services for the satellite assembly shop-floor

Production services for a satellite assembly shop-floor can be divided into three categories. (1) Manufacturing resource management services. It consists of personnel management, material management, and equipment management. (2) Production activity planning services. It comprises two categories: one is assembly shop-floor production scheduling, and the other one is material distribution and path planning. The shop-floor scheduling consists of two parts, i.e., static shop-floor scheduling and dynamic shop-floor scheduling. The material distribution and path planning also incorporates static and dynamic types. According to driving factors, it consists of proactive distribution and passive distribution. (3) Production process control and optimization services. The following are detailed functions of production process control and optimization services. (a) Product quality control and optimization. Product quality includes product geometric accuracy, physical characteristics, function characteristics, and performance characteristics. (b) Production progress control and optimization. (c) Manufacturing resource control and optimization. It includes logistics monitoring and control, personnel status monitoring and control, and equipment status monitoring and control. (d) Assembly station status monitoring and configuration optimization.

When a worker completes an assembly procedure of a satellite, procedure-related data (such as measuring data, progress data, implemented material data) must be collected before the operation of the next procedure. By comparing the planning progress and the actual progress, the service/application platform uses heuristics or meta-heuristic algorithms (e.g.,

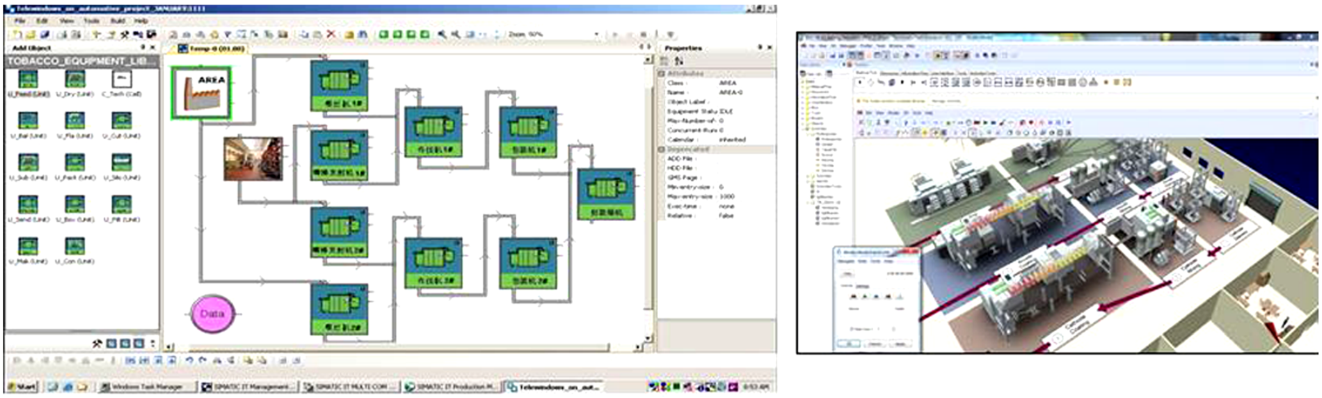

Fig. 8 Sketch interfaces of constructing a digital twin for a satellite assembly shop-floor

GA, TS, PSO) to implement dynamic scheduling of the assembly plan with the current condition of manufacturing resources, e.g., personnel status, equipment operation condition, equipment utilization condition, material inventory, and logistics status. Moreover, through the comparison of product design and measured values, dynamic compensation of product accuracy can guarantee product quality. Below we take the tolerance analysis of the optical system in a satellite as an example to illustrate the process. First, the detect system in the physical world will transmit the collected measured/test results to the product digital twin in virtual space and compare them with the design target. Then, the manufacturing error and the assembly adjustment error can be calculated and analyzed based on the consistency. The process compensation can be evaluated in the process parameter calculation module. Afterwards, the processing errors and equipment error are compensated and controlled according to the requirements of system stability and consistency. Finally, the overall system compensation performance can be evaluated. The personnel can drive the actuator to complete compensation through the assembly operation. Alternatively, through optimizing the assembly parameters, it is possible to predict the final optical performance, anti-vibration, and warm red ability of the system according to the measured data. Therefore, the personnel can make preventive decisions following the prediction results.

6.2.4 Feedback operation of the physical assembly shop-floor

In this step, the optimal schedule of production activity plan generated by the shop-floor service/application platform is fed back to the physical assembly shop and drives its operation. In the operation of the physical assembly shop-floor, a large amount of production process data and real-time data will be generated. It enables real-time acquisition and organization of the physical assembly shop-floor data. Thus, the operation phase is a continuous process with the characteristics of dynamic adjustment, iterative optimization, and closed-loop

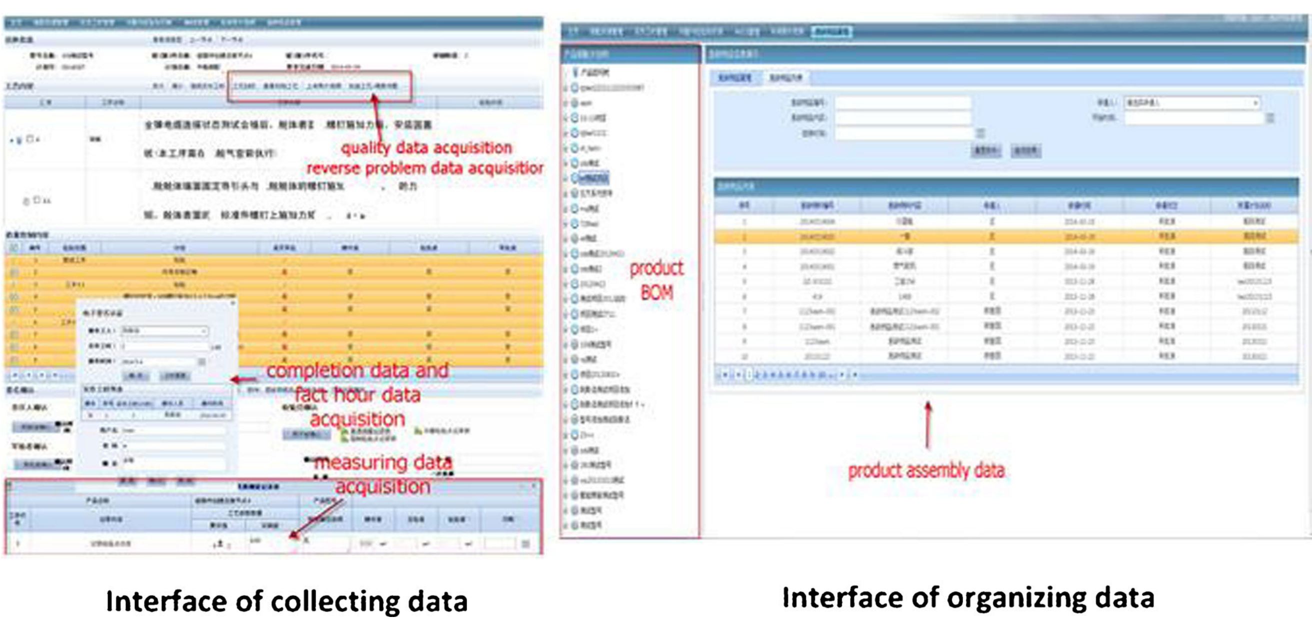

Fig. 9 Interfaces of collecting and organizing a satellite assembly shop-floor data

control. In this process, the allocation of manufacturing resources, the progress of production activity plans, and the logistics efficiency of the satellite assembly shop-floor tend to be optimal or near optimal. It can reduce the negative impact of shop-floor uncertainties and play an important role in reducing the assembly cost. Meanwhile, it can control product quality, improve productivity and production efficiency, and ensure the delivery rate. For example, due to the advent of production disturbances, the original schedule of an assembly plan is invalid and the dispatcher should reschedule or adjust the plan accordingly. Then, the newly made schedule is sent to the physical assembly shop-floor. Thus, the corresponding materials can be conveyed to the appointed assembly station. Workers in the shop-floor may conduct assembly operation using these materials and collect implement material data. Afterwards, the checkers measure and record the values of key parameters of the product. When a procedure is fully completed, workers and checkers collect completion data and work-hour data. If disturbances occur and cause a significant delay of the plan in the operation process, the dispatcher will reschedule or adjust the plan again in the service platform and send the updated plan to the physical shop-floor to guide the production.

7 Conclusions and future work

In recent years, with rapid development of new-generation information and communication technologies, such as IoT, big data, mobile Internet, and AI, the era of big data has arrived. Meanwhile, as the key technology of CPS, digital twin has gained wide attentions from domestic to international scholars and companies. Thus, it is of importance to apply digital twin and big data technologies to the manufacturing field to promote the implementation of smart manufacturing in the assembly shop-floor.

The main contributions of this paper are as follows. (1) It provides prediction services for a satellite assembly shop-floor by integrating digital twin and big data technologies, which promotes the realization of predictive manufacturing in the product assembly stage. (2) We propose a framework of digital twin-based smart production management and control for a satellite assembly shop-floor, which is a feasible and novel solution to the implementation of a smart assembly shop-floor. (3) We present a case study to illustrate how to apply the proposed framework practically in a satellite assembly shop-floor.

This study attempts to explore the application method of digital twin-based smart production management and control for the complex product assembly shop-floor. At present, this research is in its infancy and still requires a lot of work. Future research on this topic needs to be undertaken as follows: (1) construction and optimization of IoT networks in a physical assembly shop-floor; (2) construction, running, and optimization of an assembly shop-floor digital twin; (3) construction of an assembly shop-floor big data management platform; (4) construction and optimization of big data-driven prediction models and algorithms; (5) modeling and implementation of smart decision-making and optimization algorithms; and (6) more applications of digital twin and big data technology in the complex product assembly shop-floor.

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