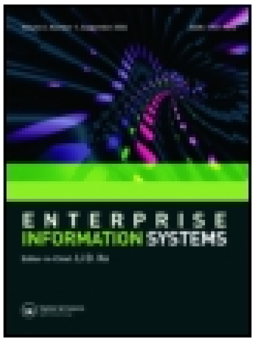

Enterprise Information Systems

ISSN: 1751-7575 (Print) 1751-7583 (Online) Journal homepage: http://www.tandfonline.com/loi/teis20

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ENTERPRISE INFORMATION SYSTEMS
https://doi.org/10.1080/17517575.2018.1526324

The modelling and operations for the digital twin in the context of manufacturing

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ABSTRACT
The lack of effective methods to develop the product, process and operation models based on virtual and physical convergence leads to the poor performance on intelligence, real-time capability and predictability in production management. This paper proposes an approach of modelling and operations for the digital twin in the context of manufacturing. Firstly, the concept and extension of the digital twin in the manufacturing context are elaborated to provide the implementation methods of virtual-physical convergence and information integration for a factory. Secondly, the modelling approaches of product digital twins, process digital twins and operation digital twins are presented, then the interoperation mode between these digital twins are explained. Thirdly, to elaborate how to execute operations between product, process and resource, Automation Markup Language (AutomationML) is used for modelling a structural parts machining cell. Finally, the performance evaluation is provided to demonstrate the improvement of production efficiency by using the proposed approach.

ARTICLE HISTORY
Received 17 January 2018
Accepted 17 September 2018

KEYWORDS
Digital twin; enterprise information integration; manufacturing operations and control; inter- enterprise interoperation; aerospace structural parts

1. Introduction

With the rapid development of information technologies in the manufacturing industry, a number of national advanced manufacturing strategies have been put forward, such as German ‘Industrial 4.0’, American ‘Industrial Internet’ and Chinese ‘Made in China 2025’ strategy. Intelligent manufacturing has become one of the directions for modern industrial development since it involves the technologies such as sensor technology, automation technology, information technology and artificial intelligence (Tao and Qi 2017). Intelligent manufacturing emphasizes the utilisation of various methods, i.e. digital modelling, simulation and experimental verification to control product design, resource allocation and production process at the workshop level (Jain, Lechevalier, and Narayanan 2017). Therefore, a lot of research work was carried out in the field of enterprise information system modelling (Wang et al. 2014, 2016), information modelling (Zhang and Li 1999; Liu et al. 2008), product modelling (Diagne, Coulibaly, and De Bertrand De Beuvron 2016), process modelling (Zhou et al. 2016) and resource virtualization (Morariu, Morariu, and Borangiu 2016). However, traditional modelling and simulation approaches in the manufacturing context are the open-loop processes. The

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principle of the production process is that the simulation goes first, followed by production activities. In the actual production process, due to the dynamics and uncertainty of the processing environment, a workshop may encounter unpredictable events or disturbances, making the original simulation results and production plans no longer feasible. Therefore, the production management and process control would have some limitations as follows: (1) lack of the real-time interaction and closed-loop feedback mechanism between physical and virtual spaces; and (2) lack of a unified product model throughout various phases in the discrete manufacturing environment for product data transmission and sharing.

In view of this situation, the digital twin has aroused the extensive attention of international academia and industry as a new research field. The digital twin technology is a core and crucial tool that enables the close integration of manufacturing information and physical resources. Digital twin refers to a digital equivalent of physical products, assets, processes and systems, which is used for describing and modelling the corresponding physical counterpart in a digital manner (Grieves 2015). It can reflect the behaviour and real-time state of its physical object accurately so that the manufacturing processes and production operations can be analysed, predicted and optimized. As a new generation technology for modelling, simulation and optimisation (Söderberg et al. 2017), digital twin technology not only emphases the importance of simulation in virtual space before production, but also allows the interaction and the execution of intelligent operations between physical and virtual spaces during production. From the perspective of the manufacturing system, digital twin-based modelling of product, process, resource and operation has a great significance for intelligent and predictive manufacturing.

The outline is organized as follows. Based on a review of related works in section 2, the concept and extension of digital twin in the manufacturing context are described in section 3. The modelling approaches of product digital twins, process digital twins and operation digital twin are detailed in section 4. Section 5 presents the operations and web-based connection among these digital twins. Section 6 gives an illustrative application and discussion to verify the proposed approach. Conclusions and future work are presented in section 7.

2. Literature review

In order to enhance the capacity of product digital design and manufacturing, digital modelling and simulation technologies have been developed rapidly in the past 20 years. Traditional static models are constructed before production, including product geometric model (Chu, Wu, and Hsu 2009), feature-based model (Li et al. 2006), product structural model (Wu and Hsu 2008) and product integration model (Coulibaly, Mutel, and Ait-Kadi 2007). However, considering the complex and ever-changing production environment, uncertain disturbances may lead to the failure of the product models. Additionally, the introduction of concurrent engineering (Li, Zhang, and Chen 2001) and collaborative manufacturing (Mu, Bénaben, and Pingaud 2013) enhanced the capability of information sharing in the product design phase. Nevertheless, the product models are relatively independent at individual phases, i.e. product design, manufacturing and service phases. Product data cannot be communicated and shared between design, process, manufacturing and service models, resulting in the problem of information island.

In addition, the current process models are also static models. Although scholars have done relevant research on process information expression techniques and process modelling methods, such as Extensible Markup Language (XML)-based process information expression technology, multi-dimensional process information modelling method. These methods just focus on generating process models in virtual space, which are hardly to make responses according to the unpredictable events or disturbances in the manufacturing systems. There is thus a need to develop the process digital twin combining with real-time data of the production site to realize proactive prediction and dynamic adjustment for process problem.

Aiming at the issues above, digital twin technology has been introduced as an effective method for the convergence of physical and virtual spaces. Professor Grieves at the University of Michigan firstly put forward the concept of 'Digital Twin' in Product Lifecycle Management (PLM) courses in 2003. At that time, the information collection approach for physical products mainly depending on manual recording on paper media. There was not enough data to describe the properties and behaviours of physical objects accurately in the virtual space. Thus, the research and application of digital twin were poor. With the advancement of information technology, the two-way real-time data transmission between physical and virtual spaces promotes the development of digital twin. In 2011, the U.S. Department of Defense applied the concept of digital twin in the health maintenance of spacecraft. Later, the digital twin was used by the US Air Force Research Laboratory to build a high-fidelity flight model for predicting the aircraft structural life (Tuegel et al. 2011). Since then, digital twin has been applied in academic research and industrial practices for modelling, virtual and physical convergence, data transmission and integration.

In the aspect of digital twin-based modelling, a number of studies have been carried out, including theoretical research on digital twin workshop (Tao and Zhang 2017; Zhuang, Liu, and Xiong 2018), digital twin-driven product design, manufacturing and service (Schleich et al. 2017; Tao et al. 2018), as well as practical research on digital twin-based production lines (Vachálek et al. 2017; Zhang et al. 2017) and digital twin-based work cell (Tavares et al. 2018). In the industrial manufacturing area, Siemens has adopted the digital twin in the production of its industrial equipment named Nanobox PC for realizing the new pattern of digital manufacturing. PTC connects physical products with virtual products based on digital twin technology to detect the problems of physical products in time, which gives a better after-sales service for customers. However, theoretical and practical research for modelling the basic production factors (i.e. product, process and resource) and production operations based on digital twin are still urgently needed, which are essential for promoting the digitization of product design, process design, production planning and manufacturing execution.

With regards to virtual and physical convergence, digital twin technology is the core component of Cyber-Physical Systems (CPS) (Negri, Fumagalli, and Macchi 2017). Relevant research has been conducted on product virtualization (Silva and Kaminski 2016), manufacturing resources virtualization (Zhang et al. 2016; Moreno et al. 2017; Cai et al. 2017; Zhang, Zhu, and Lv 2018) and process information collection and control optimization (Liu et al. 2016, 2017). At present, the interaction mode between physical and virtual spaces is mainly off-line interaction, lacking continuous and online interaction.

In the aspect of data transmission and integration, AutomationML can model digital twin-related properties for data exchange between different systems during the application process of digital twin technology (Schroeder et al. 2016). In addition, web service can be used as a method for accessing data from a digital twin (Schroeder et al. 2017). A digital twin-based production system was also developed using real-time data acquisition and processing technology (Uhlemann et al. 2017). Data-driven intelligent prediction provided support for the predictive manufacturing (Wang, Zhang, and Wang 2017, 2018). Although real-time data acquisition and transmission technology supports the interaction between physical space and virtual space, implementing feedback control based on two-way transmission and real-time analysis is still challenging.

Based on the foregoing observation, the current application of digital twin is still in an initial stage while the development of product digital twins, process digital twins and operation digital twins has great potential for improvement. In the future, each production factor will have a precise model in the virtual space. The modelling and operations for the digital twin in the context of manufacturing play a significant role in production operation optimization and management.

3. The concept and extension of digital twin in the manufacturing context

3.1. Concept

The intelligent factory is the core of intelligent manufacturing at the factory level (Ding et al. 2016). At present, information systems in the factory are developing toward the collaborative and intelligent direction (Teoh, Yeoh, and Zadeh 2017; Al-Tit 2017), and they have been able to realize the overall management of enterprise resources and product data. Figure 1 shows the digital twin framework for factory automation. Using digital twin technology, data collected and recorded by the information system is displayed in the virtual factory to detect, analyse, control and optimize in the specific scenarios, so as to improve the performance of the physical factory. Digital twin technology is a method or tool for modelling and simulating a physical entity's status and behaviour. It can realize the interconnection and intelligent operation between the manufacturing physical space and virtual space. Through utilizing digital twin technology, all factors in the physical factory are defined accurately. Relevant information related to production activities in the physical factory are reflected and verified digitally in the virtual factory. Thus, dynamic changes can be communicated between physical units (i.e. product, plant or factory) and its virtual models with real-time feedback generated. It should be noted that the virtual factory is not independent as it connects the physical factory in real time. The factory digital twin is a higher-level virtual model based on virtual and physical convergence. As mentioned above, digital twin, as a virtual model in the virtual space is used to simulate the behaviour and characteristics of the corresponding physical object in real time.

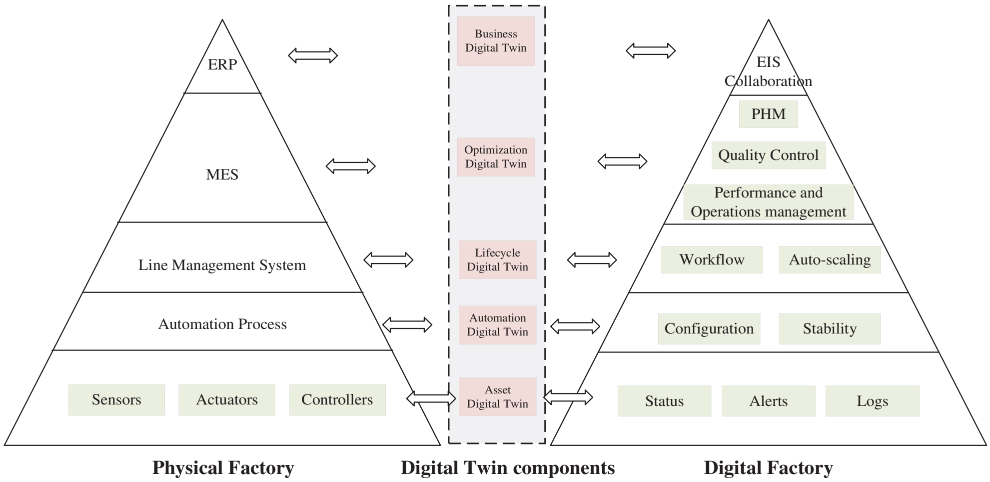


Figure 1. The digital twin framework for factory automation.

3.2. Extension

The current information integration application of factory mainly relies on single information system, which is insufficient for considering and integrating the data of upstream business (such as product design) and downstream business (such as product service). Digital twin technology provides an effective solution for data management during product design, manufacturing and service process. The material flow, information flow and business flow are integrated by accessing data from each phase of the product lifecycle. The extension of digital twin technology is to integrate lifecycle information for developing a unified product virtual model at the upstream of manufacturing. Then, at the downstream of manufacturing, this virtual model will be expanded to the phases of product maintenance and service, and even product recycling. Thus, automation pyramid shown in Figure 1 is transformed into a cloud computing schema and flattening (Puttonen et al. 2016) and digital twins are extending to both ends of the manufacturing context, as shown in Figure 2. In the manufacturing context, virtualizing all types of resources, processes, operations, behaviours and services to form a manufacturing-oriented digital twins cloud by taking full advantage of the flattened organization of the factory. Unified and centralized optimization management of the digital twins cloud is conducted for completing various activities intelligently. Meanwhile, the integration and optimization of the business processes, information systems and enterprise resources are conducted, which can realize synergy throughout the phases of product design, manufacturing and service. The mechanism of information integration promotes the innovation of factory.

With the wide application of information and manufacturing technologies such as industrial internet (Li et al. 2017), cloud computing (Liu et al. 2018a), big data (Wang and Zhang 2016; Wang et al 2018), internet of things (Bi 2017) and mobile internet (Shi et al. 2016) technology, the development of real-time virtual-physical interactive connection between physical and virtual spaces has received continuous technical support. According to the characteristics of virtual-physical interaction and digital management

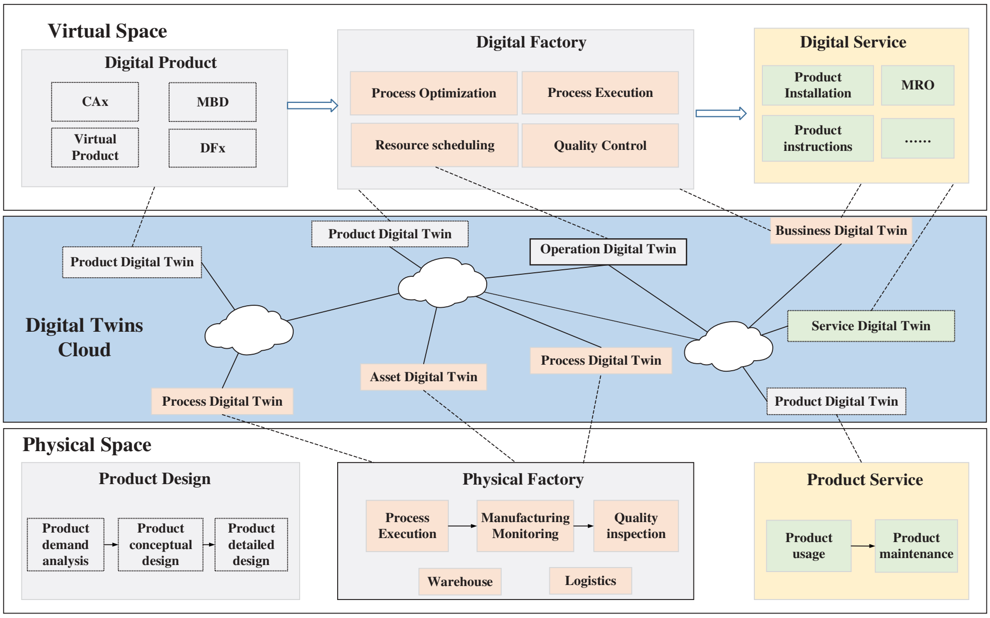


Figure 2. Digital twins extend to both ends of the manufacturing context.

of the digital twin technology, there are three distinguished enabling technologies for the development of a digital twin-based factory.

(1) Virtual-physical integrated. Related technologies include real-time virtual-physical interactive technology, virtual-physical mapping technology, multi-dimensional/scale model integrated and syncretic technology, virtual reality and augmented reality technology.

(2) Big data-driven. Related technologies to implement big data-driven production include massive-multi-dimensional-heterogeneous manufacturing data pre-treatment technology, big data processing technology, big data temporal analysis technology, multi-scale/sequential analysis technology, data network modelling and correlation analysis technology, data cleaning and mining technology, data visualization technology.

(3) Real-time operation optimization. Key technologies for intelligent production operation include collaborative operation technology, production operation analysis and forecast technology, quantitative control-based production operation decision technology, 'monitor-forecast-regulation' decision-making technology.

4. An integrated manufacturing information model using digital twins

From the shop floor manufacturing process perspective, there are mainly three digital twin's models: *Product Digital Twins, Process Digital Twins, and Operation Digital Twins*. These digital twins are developed at different levels and then integrated for collaborative control of 'people-machine', 'machine-machine' and 'machine-object' in the workshop (Tao et al. 2018).

4.1. Product digital twins

The Model Based Definition (MBD) technology (Ruemler et al. 2017; Liu et al. 2018b) provides the product digital twin with a digital manufacturing information carrier in the design phase, the manufacturing phase and the Maintenance, Repair & Operations (MRO) phase. After adopting MBD technology, the three-dimensional model serves as the single data source. Process design, tooling design, part processing and part inspection are implemented based on MBD data, which can achieve parallelization and collaboration of product design, manufacturing and service. The product definition model mainly includes two kinds of data: (1) geometric information, which is the product design model; and (2) non-geometric information, which is stored in the standard tree structure.

Figure 3 presents the construction process of the product digital twin at the product design, manufacturing and MRO phases. The product digital twin at design phase utilizes an integrated three-dimensional entity model to define product information (i.e. geometrical information, non-geometry information and management information) after considering design constraints. The predefined information can meet the needs of data for simulation, NC (Numerical Control) programming, production and testing. The product digital twin at design phase is described by a tree structure, whose tree nodes represent the information contained in the digital twin. After the process of reconstructing the product design model, the product digital twins at manufacturing phase are developed after considering the constraints of the process route and resources. In the manufacturing phase, the product digital twins are composed of a set of models from the raw material to a finished product. Each procedure in the processing route generates an intermediate model, which is called procedure model. Each node in the tree structure refers to a single procedure model. Different procedure models define various manufacturing information based on processing requirements, i.e. processing equipment

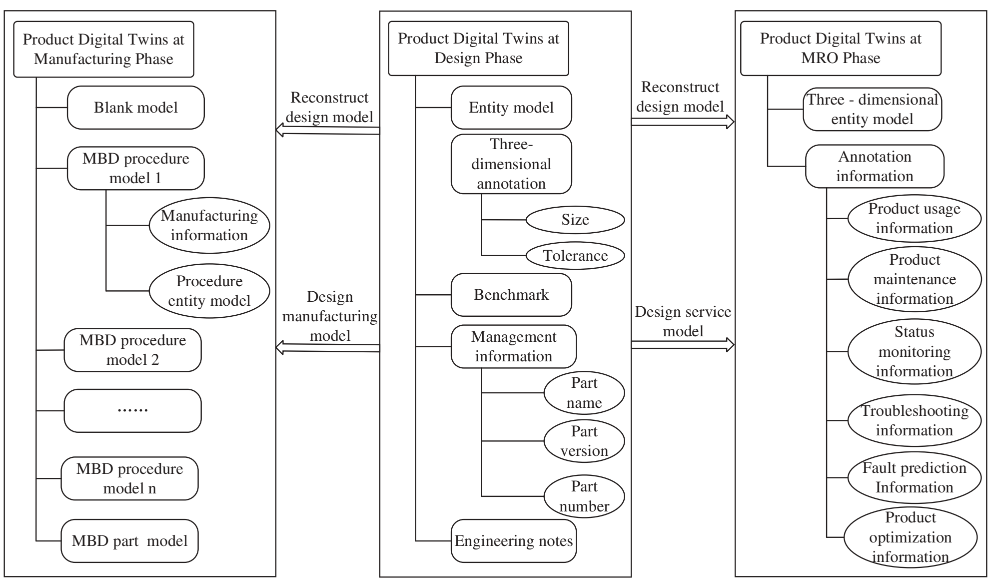


Figure 3. The construction process of the product digital twin based on MBD.

information, tooling information, process information and test information. The manufacturing information can be associated with each procedure model through the procedure design table or three-dimensional annotation. Similarly, the product digital twin at the design phase can be reconstructed for developing product MRO model. Product digital twin at MRO phase mainly include three-dimensional entity model and annotation information. For instance, the cause and the location of the failure in the use phase of the product are directly associated with the three-dimensional model in the virtual space through the three-dimensional annotation.

In summary, product digital twin associates multi-dimensional, multi-scale information with a complete three-dimensional model throughout the product design, manufacturing and MRO phases. This unified product model will significantly enhance the ability to transfer and share information between each phase. The product digital twins are constructed to simulate and monitor the physical products' behaviour and state, which can also promote the decision-making control towards the physical space.

4.2. Process digital twins

The product design model describes the final version of the product without detailed manufacturing requirements. Therefore，a process digital twin is required to support the production processes. The process digital twin is the core which connects the product design and manufacturing processes. Process digital twins are presented as three-dimensional models throughout the manufacturing process, including manufacturing procedure model, process attribute information and asset digital twins. Process digital twin can be expressed as:

$$PDT = PAI \cup \sum_{i=1}^{m} MPM_i \cup \sum_{j}^{n} ADT_j$$

in the formula:

PDT – Process digital twin;

PAI – Process attribute information, refers to the product name, product lot number and product version, etc.;

MPM_i – Manufacturing procedure model，a single process digital twin contains multiple procedure models;

ADT_j – Asset digital twins，including machine tools, cutting tools and other resources.

Assets are the most basic execution unit for workshop production activities. Asset digital twin uses an integrated three-dimensional model to fully express the physical properties (i.e. size, shape, running parameters, processing capacity) of the corresponding asset. By building the internet of manufacturing things in the production site, information (i.e. real-time temperature, torque, electric current and power, etc.) can be obtained through the Programmable Logic Controller (PLC) of a machine tool. In addition, parameters (i.e. vibration signals and cutting force) can be obtained by installing sensors on a machine tool. The multi-type, multi-scale data collected from physical assets is extracted, cleaned and parsed, and the processed data is stored in the database for implementing interaction with the asset digital twins. Figure 4 shows the description of asset attribute information in ADT_j. Real-time data collection services enhance the

```
<?xml version="1.0" encoding="utf-8" ?>
<XML Representation version="1.2" xmlns="http://www.3ds.com/xsd/3DXML" >
<Processing_Equipment   Name=”Machine”   ID=”A3001”>
  <Attribute>
    <Name> Spindle_speed < /Name >
    <PLC> Spindle_speed_PLC</ PLC >
  </Attribute>
  <Attribute>
    <Name> Spindle_Power < /Name >
    < PLC > Spindle_Power _PLC</ PLC >
  </Attribute>
  <Attribute>
    <Name> Load < /Name >
    < PLC > Load_PLC</ PLC >
  </Attribute>
  <Attribute>
    <Name>Torque< /Name >
    <Sensor>Torque_Sensor</Sensor>
  </Attribute>
</ProcessingEquipment>
```


Figure 4. Asset attribute information in $ADT_{j.}$

perception ability of physical manufacturing resources and enable mapping between physical assets and asset digital twins. Asset digital twins can realistically simulate the running state of the physical assets through the three-dimensional model, so workers can easily understand the machining state of workpieces. Meanwhile, combined with data analysis algorithms and machine learning, the asset's processing behavior model, cooperative behavior model and fault behavior model are established to support intelligent applications such as fault diagnosis and life prediction.

Figure 5 demonstrates the model of the process digital twin. Based on process information model, the process digital twin integrates three key elements effectively, which are the interface, computing and control attributes.

The interface is used to implement communication between physical and virtual spaces, and between process digital twins, product digital twins and operation digital twins. For example, web service technology(Du, Gai, and Zhou 2017) provides a unified data access interface for process digital twin. On the one hand, physical space can access simulation data from the process digital twin by using web service. On the other hand, process digital twin can simulate and reflect the machining status of the workpiece in real time by accessing machine operation data. In addition, in order to develop process digital twin, manufacturing features are extracted from the product digital twin using feature recognition software. Therefore, both web service and feature recognition software are the interfaces that enable interaction.

In the model, computing refers to the computability of the digital twins. The process digital twins can provide services for the production process, such as interference checking, program verification, process optimization, quality prediction. For example, the collected data (i.e. spindle speed, cutting force, and workpiece vibration signal of the machine tool) can be mapped to the process digital twin, combining with the intelligent

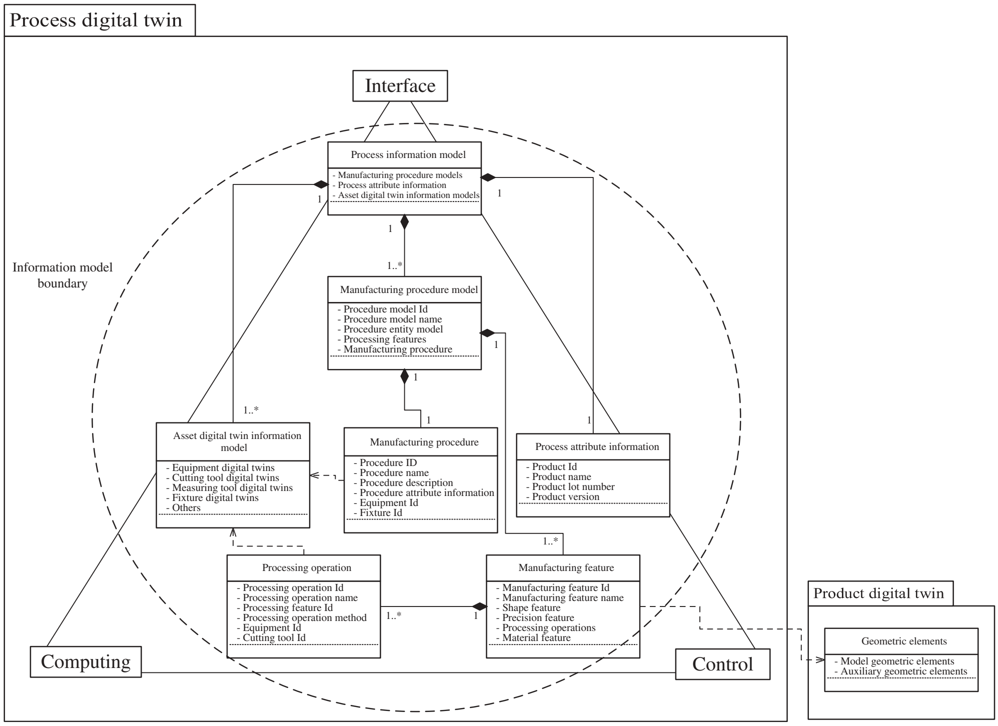


Figure 5. Model of process digital twin.

algorithms (i.e. deep neural network, convolutional neural networks), the surface roughness of the workpiece can be predicted so as to the processing quality.

The function of control is to evaluate, optimize and predict the production process based on real-time simulation data, real-time production data, and historical production data. According to the simulation and analysis results, the real-time controlling instructions are fed back to the physical space for optimizing the production process. Taking the error analysis as an example, the error analysis algorithm is used to calculate the manufacturing error between the work in process (WIP) and the process digital twin based on the virtual-physical consistency principle. The calculated error of the machine tool or the cutting tool is dynamically compensated to ensure the quality of the production.

In the model of process digital twin, process information model takes the manufacturing procedure model as a carrier. The three-dimensional annotation information and process information are defined in the manufacturing procedure model. The annotation information of the procedure model defines procedure dimensions, surface roughness, processing requirements, etc., which are associated with the geometrical information. A manufacturing procedure model includes multiple manufacturing features. The manufacturing feature describes the area that needs to be machined on the procedure model. The information such as machining method, machine tool and cutting parameters to be used for machining each feature is bound to the corresponding features. The manufacturing features are extracted from the product digital twins.

4.3 Operation digital twin

4.3.1 The model of operation digital twin

Operation digital twin is used to simulate and analyse the interactive behaviours (i.e. people-machine, machine-machine and machine-object) between production factors. The performance and execution condition of various operations (i.e. resource scheduling operation, production process management operation and equipment health management operation) can be monitored by using digital twin technology. In this research, four models are integrated to generate a precise ontology-based operation digital twin metamodel, which are petri net-based process behaviour model, Systems Modelling Language (SysML)-based collaborative information model, Predictive Model Markup Language (PMML)-based decision-making model and operation visualization model, as shown in Figure 6. These four models provide information for operation digital twin metamodel from different perspectives and form a logical unity based on model fusion and attribute mapping rules.

Since the interactive behaviours in production site are various and dynamic, operation digital twins should be flexible, customised and dynamic. By configuring the parameters and mapping relationships between the four models, different operation digital twin metamodels are defined. In this way, different granularity processing tasks can be simulated and monitored. The development process of the operation digital twin is described as follows:

(1) Process behaviour model is built to describe the machining behaviour in the production process. It defines the behavioural characteristics of the operation digital twin metamodel. The petri net-based process behaviour model can clearly describe the dynamic machining process of the product by analysing the energy flow, material flow and information flow. It is used as a driver for the operation digital twin metamodel, collaborative information model, decision-making model and operation visualization model.
(2) The collaborative information model is a description of the collaborative behaviour between disparate asset digital twins. In the actual production process, limited resources and potential equipment failures make it necessary for various resources to be collaborated with each other to accomplish tasks together. As a standard modelling language for systems engineering, SysML can model the interactive behaviours between different assets. Collaborative information model simulates the collaborative behaviour of the physical assets, which results in the dynamic and robust cooperation between multiple assets. It provides a new mode for information interaction, business collaboration and process control between different digital twins, and optimizes the allocation and configuration of manufacturing resources within the constraints.
(3) The decision-making model correlates the computing attributes of operation digital twin metamodel, making it capable of evaluating, reasoning, and validating. In general, the decision-making model consists of input variable, algorithm library and constraint rule library. The input variable can be either numerical or ordinal. The algorithm library serves as the engine of the decision-making model in which various types of algorithms are encapsulated in the form of dynamic link library. The constraint rule library stores constraints and rules related to the production

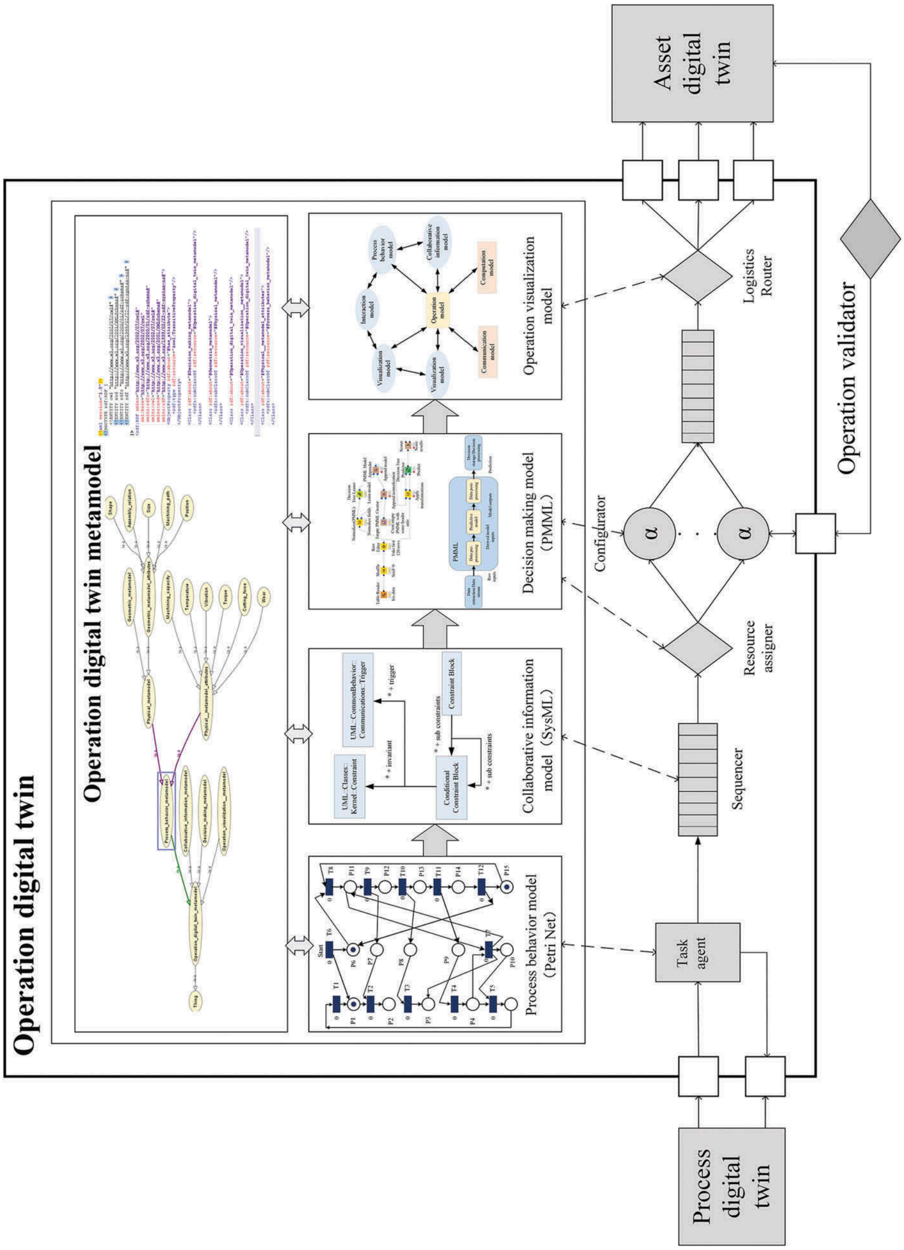


Figure 6. The model of operation digital twin.

processes, such as the constraint of the processing capability of a certain equipment and the Automated Guided Vehicle (AGV) scheduling rule of the workshop.

(4) The operation visualization model is the human-computer interaction interface of the operation digital twin metamodel. By configuring the mapping relationship between the operation visualization model and the operation digital twin metamodel, the execution status of the processing task is reflected and displayed dynamically in the form of visualization.

After the definition of each model is completed, serialize the data structure and the logical mapping relationship between the four models to form an ontology model. This ontology model is called the operation digital twin metamodel. Based on practical requirements, an operation digital twin metamodel database can be developed to design different processing behaviours. The operation digital twin metamodel database can be imported and exported to configure processing tasks. After the configuration, relevant files are serialized and stored. Users can retrieve and deserialize the configuration files at any time, so as to realize visual simulation of different processing tasks.

Figure 6 gives an application mode of how the operation digital twin simulates and analyses the interactive behaviour. The specific processes can be described as follows.

Step 1. Process digital twin publishes machining task information of a workpiece to the task agent through interfaces.

Step 2. The task agent generates an initial task execution sequencer according to the task requirement.

Step 3. Considering the constraints of the resource, the configurator sets each procedure's weight of the task and then generates an optimized sequencer.

Step 4. The logistics router allocates materials according to the optimized sequencer. The task information is published to the asset digital twins for simulating the machining process through the interfaces. Operation digital twin analyses the whole process and provides intelligent analysis and control services.

4.3.2 The interoperation among digital twins

Interoperability is the ability of two or more systems to exchange information and use the exchanged information (Geraci et al. 1991). In this research, the interoperation is a process for implementing transmission and sharing of data, information and knowledge among digital twins. The data bus with digital twins is a communication system that enables the digital twins of various processes to synchronize and transfer data. The data bus can exchange and manage information of digital twins, enabling the two-way interaction, information sharing and value chain collaboration. As shown in Figure 7, data bus enables the information communication between different processes, so that data is synchronized and communicated between digital twins in real-time.

5. Operations in the manufacturing context based on digital twin

Following the object-oriented information storage approach, AutomationML allows the physical and logical components of a production system to be modelled as data objects.

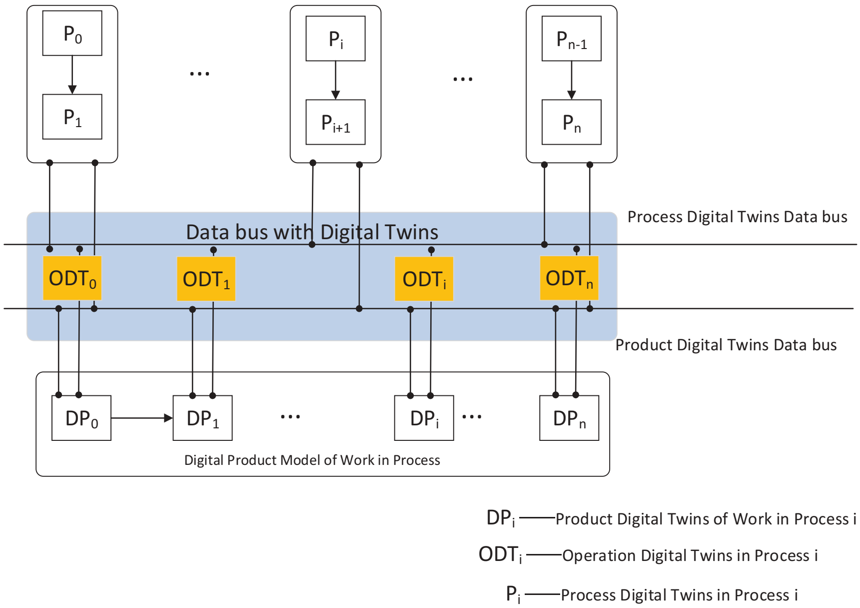


Figure 7. The interoperation among digital twins.

Each object contains topology, geometry, kinematics, logical (sequencing, behaviour, and control) information and other attribute information. In this research, AutomationML is used to model the machining cell, focusing on the resource, process, and product. The specific process can be explained as follows.

Step1: Process Phase. *The objects of the machining cell are collected as internal elements from the perspectives of the resource, process and product.*

```
    Input: Process digital twin sets
      Enum: Elements_DTsets [i]
        for t ← 0 to i
          InternalElement1_name ← InternalElement1[t].name
          do Interface_OperationDT(InternalElement1_name)
        end for
      Validate:
        If ProcessDT! = true
          Continue
```

Step2: Operation phase. *Determine the semantics of operations.*

```
    for t ← 0 to i
      for s ← 0 to j
        foreach parameters in confSets
          if a[parameters] ∩ router[t] ∩ sequence[s] = = true
            Evaluate(DT [s],DT [t],..)
          If isOperatable = = true
            Execute(DT(i))
      end if
      end for
```

Step3: *Action phase and Feedback phase. Submit the operation task and get feedback, connect all internal elements.*

```
      Input Resource[Num_i], Process[Num_j], Product[Num_k]
      if RoleClass = = Resource then
        for t ← 0 to Num_i
          do RoleClassModeling(Resource[t].name)
          do RoleClassModeling(Process[s].name)
            do SCADA
              if warning = = occurred
                go Step2
          end for
        end if
```

The AutomationML model of the structural parts machining cell is shown in Figure 8. The internal elements of resource, process and product are connected to each other in their separate sets by Product, Process, Resource Connector (PPRConnector) interfaces. For example, the PPRConnector of rough processing, machines and WIP are interconnected, indicating that the rough processing of the WIP is implemented by a related machine tool. The rule interface of the rough processing and the sequence interface of machines are interconnected to indicate that the process rule of rough processing constraints the usage sequence of machines. The elements in Figure 8 are connected by dashed lines in the form of <internalLink>. By correlating the internal elements of resources, products and processes, AutomationML describes a complete machining cell. The introduction of AutomationML data exchange format and the development of a unified AutomationML database enable the information integration between different digital twins.

Industrial Internet realizes comprehensive sensing, dynamic transmission and real-time analysis of data by constructing a network connecting operation, product, process and asset digital twins (as shown in Figure 9). In a single digital twin, the attributes of interface, computing and control are integrated and interconnected. As described, the purpose of the interface is to implement communication. The development of Supervisory Control and Data Acquisition (SCADA), OPC Unified Architecture (OPC UA) and MTConnect technology enables the digital twins to access real-time data from the production site. The computability of digital twin is characterized by the ability to

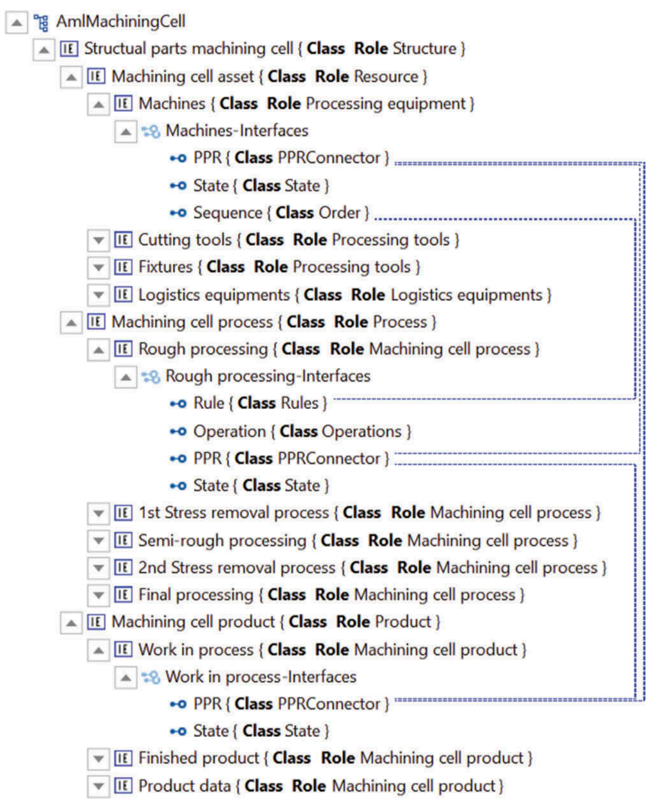


Figure 8. The AutomationML model of structural parts machining cell.

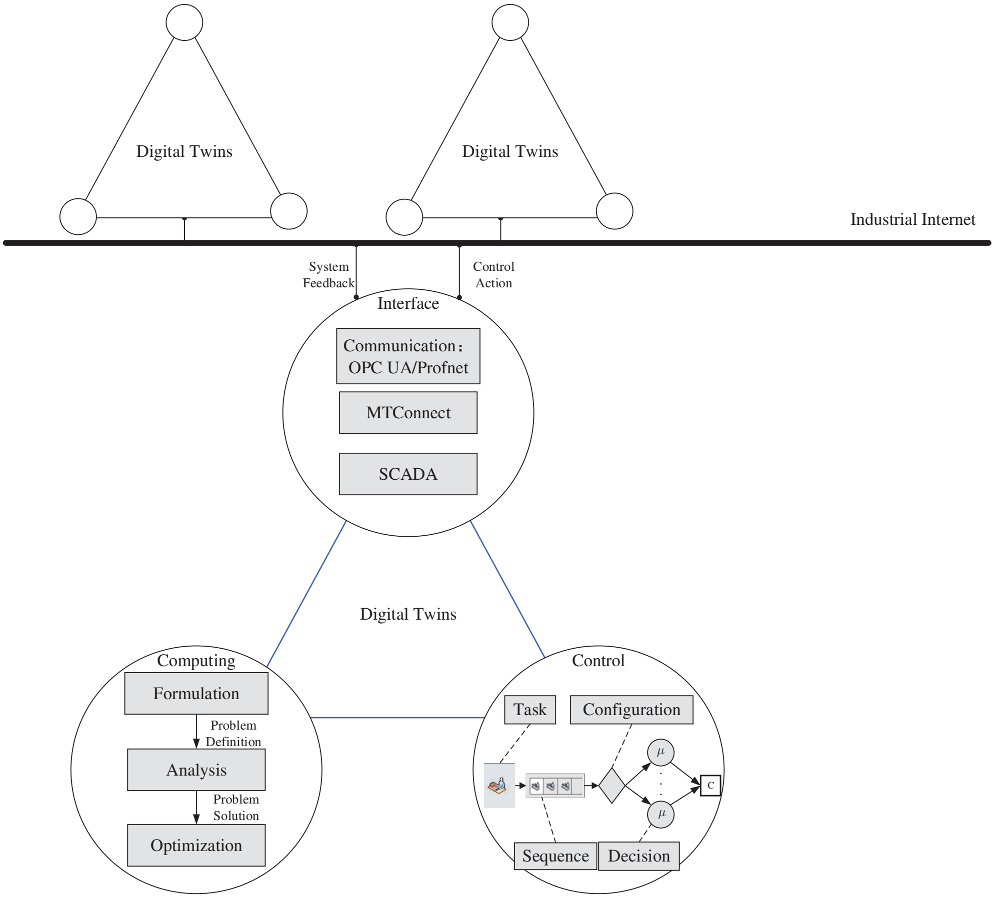


Figure 9. Web-based connection among digital twins.

analyze, optimize and validate different production activities. Control attribute can be implemented in the form of controlling orders, making the production process controllable, adjustable and predictable. For example, the operation digital twin is capable of optimizing the task execution sequence, controlling the resource allocation and providing decision-making support. The operations in the manufacturing context include various types, i.e. planning, computing, controlling and interacting. Thus, through the collaboration of different digital twins, the simulation and iterative optimization of physical manufacturing activities can be completed. Data bus enables data transfer between product digital twin, process digital twin and operation digital twin. Furthermore, a web-based connection is developed between different digital twins through the Industrial Internet. The Industrial Internet provides them with an intermediate mechanism of achieving interaction and collecting feedback.

6. Performance evaluation

Taking the production process of aerospace structural parts as the example, the feasibility of applying digital twin technology to the structural parts machining cell is analysed. Firstly, the structural parts digital twins, the machine tools digital twins and the tooling digital twins are constructed. The structural parts digital twins provide the three-dimensional model, Engineering Bill of Material (EBOM), manufacturing features and attribute information to the Computer Aided Process Planning (CAPP) system utilizing the interfaces of digital twins. Then the process design is carried out in the CAPP system, which defines the process digital twins. Secondly, process digital twins provide Process Bill of Material (PBOM) to the three-dimensional Computer Aided Manufacturing (CAM) system for configuring the virtual processing environment. Using the NC machining simulation system, NC code can be generated for production simulation in the virtual machining cell. Thirdly, the virtual machining cell produces an initial production plan. During the production process of the physical machining cell, the real-time running state of the machine tool can be obtained through the NC system and sensors, and the state information of the WIP can be obtained by Radio Frequency Identification (RFID). After receiving these data through interfaces, the digital twins of the structural parts and machine tools in the virtual machining cell update their status to simulate the physical changes. At the same time, the virtual machining cell modifies and optimizes the production process. The controlling instructions are released to the physical machining cell in real time to adjust the production plan. Through the continuous iteration of this process, the production state of the physical machining cell is optimized. Real-time analysis and optimization for the operations in the whole process are achieved by the operation digital twins. After the completion of the production process, the finished structural parts are put to use if they meet the requirements of the pre-built structural parts digital twins. In the usage process of the structural parts, relevant date (i.e. location data, maintenance data, fault data) is collected and then transmitted to the structural parts digital twins to optimize their models.

The physical machining cell collects real-time data during the production process by utilizing RFID, sensor, numerical control system, etc. Multi-source heterogeneous data generated by the physical machining cell is standardized, encapsulated and transferred to the virtual machining cell through the interfaces. The WIP simulation data and the machine tool simulation data in the virtual machining cell can be obtained from the structural parts digital twin and the machine tool digital twin while the other data of virtual machining cell can be acquired from the information management system (i.e. Enterprise Resource Planning (ERP), Product Data Management (PDM), etc.). The information integration method based on the digital twin technology not only collects information in the physical machining cell but also integrates the information of the virtual models.

In this paper, the application process of digital twins is validated by 5 different structural parts whose manufacturing procedures and features are various (as shown in Table 1).

The manufacturing performance of Part A by using manual + NC machine, automatic flow line and manufacturing with digital twins are compared in Table 2. Performance indicators include execution time, total running time, downtimes, quality inspection batch and logistic accuracy rate. After simulating the production plan of Part A, its production process and process route are optimized. However, there is great uncertainty in regard to the factors (i.e. machine waiting time, machine adjustment time, processing method, process route, and machine tool allocation for each procedure, etc.) under the mode of manual + NC machine. Therefore, compared to the manual + NC machine, the execution time and total running time are reduced significantly under the mode of manufacturing

Table 1. Parts and requirements of processes.

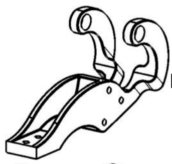
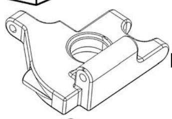
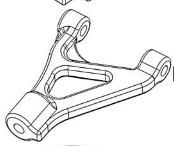
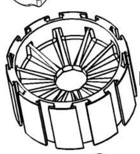
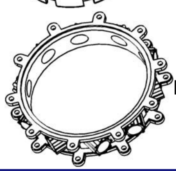
Parts	Number of procedures	Indicators of manufacturing
 Part A	4 procedures Manufacturing features: 6 holes and 3 planes	Deadline: 40 min FPY (First-Pass Yield):97%
 Part B	6 procedures Manufacturing features: 4 holes and 1 plane	Deadline: 50 min FPY:97%
 Part C	6 procedures Manufacturing features: 3 holes and 4 planes	Deadline: 60 min FPY:97%
 Part D	12 procedures Manufacturing features: 10 notches and 2 cylinders	Deadline: 90 min FPY:95%
 Part E	21 procedures Manufacturing features: 2 holes, 2 planes,1 cylinder	Deadline: 135 min FPY:99%

Table 2. Performance comparison different manufacturing mode.

	Manual + NC Machine	Automatic flow line	manufacturing with digital twin	comments
Execution time	36 min	18 min	19 min	Deadline:38 min
Total Running time	43 min	28 min	23 min	Manufacturing phase
Down times	1	4	0	machine down times per day
QI batch	128 pieces sample size: ALL	32 pieces	4 pieces	Quality inspection batch per day
Log. accuracy rate	95.5%	96.6%	99.2%	Logistic no wait times

with digital twins (as shown in Table 2). The execution time of manufacturing with digital twin and automatic flow line is similar. From the perspective of down times, asset digital twins simulate and monitor the running state of machine tools in real time through analyzing real-time machine running data and give instructions to adjust the parameter configuration of the machine tools. Thus, the problems that may encounter in the production process are avoided so that the machine downtimes per day are greatly reduced. In addition, by testing whether the high-fidelity process digital twins meet the processing requirements, the quality of the WIP is verified after each procedure is completed. The quality inspection batch per day is reduced greatly because only several key manufacturing procedures are required to be inspected using precision measuring instruments. After the resource allocation plan and parts processing sequence are simulated and optimized in virtual space, materials are delivered to locations by AGVs accurately. Therefore, the logistic accuracy rate is increased by about 4%.

In order to further analyze the performance of manufacturing with digital twins, the execution time and quality inspection batch of the 5 different structural parts are compared under the three different manufacturing modes (as shown in Figure 10). Compared with the manual + NC machine, manufacturing with digital twins reduces the execution time by an average of 20%. Compared with the automatic flow line, the execution time of the manufacturing with digital twins has a very small variation. It is noted that the manufacturing with digital twins has obvious advantages in reducing quality inspection batch compared to the automatic flow line and manual + NC machine, especially in the case with a large number of parts.

In conclusion, manufacturing with digital twins can effectively reduce quality inspection batch, improve logistics accuracy rate and reduce machine down times, which is significant for aerospace structural parts with high-quality requirements.

Conclusion and future work

Under the background of 'Industrial 4.0', the digital twin technology has been widely used as a tool to realize the interaction and interconnection between physical and virtual spaces. Aiming to converge the physical space and the virtual space in the current workshop and factory, this paper develops three kinds of digital twins (including product digital twin, process digital twin and operation digital twin) in the context of manufacturing, which can simulate the state and behaviour of the corresponding physical object digitally for optimizing production process. The main contributions of this paper can be summarized as follows:

(1) It provides the methods of constructing the product digital twin and process digital twin. The product digital twin is constructed by a unified model throughout the product design, manufacturing and MRO phases, so that information can be communicated and shared between different phases. By integrating interface, computing and

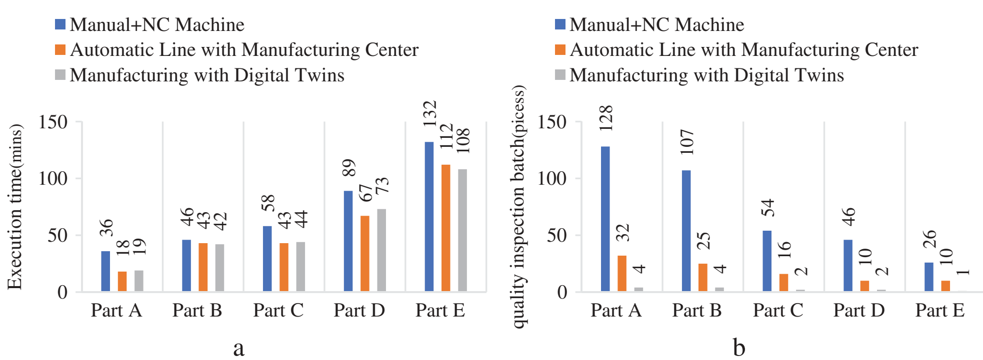


Figure 10. (a) Execution time. (b) quality inspection batch for manual, automatic line, and digital twin enabling manufacturing considering different application deadlines and quality inspection process.

control attributes, process digital twin promotes the interconnection and convergence between physical and virtual spaces in the production process.

(2) The operation digital twin metamodel is developed based on multivariate model fusion. Through the flexible combination and integration of multiple operation digital twin metamodels, various interactive behaviour can be simulated and analysed.

(3) This paper designs an AutomationML model of structural parts machining cell, which is a novel method to execute operations between product, process and resource in the manufacturing context.

This paper focuses on the modelling and operations (including planning, computing, controlling and interacting, etc.) for the digital twin in the context of manufacturing. And the future work can be addressed from two aspects: (1) utilise both digital twin technology and big data for predictive manufacturing and (2) undertake workshop-oriented modelling and operation based on digital twin technology.

Disclosure statement

No potential conflict of interest was reported by the authors.

Funding

This work was supported by the National Natural Science Foundation of China [51475301];the Fundamental Research Funds for the Central Universities [2232017A-03].

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