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ORIGINAL ARTICLE

# Information modeling for cyber-physical production system based on digital twin and AutomationML

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**Abstract**

Production systems play an important role in intelligent manufacturing. A large number of manufacturing resources are designed and developed with virtual (digital) ones, which will be associated with the physical ones throughout their lifecycle. With the recent emergence of information and communications technologies (ICTs), such as internet of things, big data, virtual reality, artificial intelligence, and 5G, the interconnection and interaction between physical resources and virtual ones become possible in production systems. Digital twin (DT) shows great potential to realize the cyber-physical production system (CPPS) in the era of Industry 4.0. In this paper, we present our vision on integrating various physical resources into CPPS via DT and AutomationML. To elaborate on how to apply ICTs, this paper firstly explores a generic architecture of CPPS based on DT. DT is a virtual and authoritative representation of physical manufacturing resource, since DT includes various models and manufacturing big data of resource. The proposed architecture is illustrated in detail as follows: (1) physical layer, (2) network layer, (3) virtual layer, and (4) application layer. A case of expert fault diagnose for aircraft engine is presented using the proposed information fusion in the architecture. Secondly, this paper proposes an approach of information modeling for CPPS based on AutomationML. Various manufacturing services can be encapsulated and defined in the standardized format (AutomationML), and then the corresponding virtual manufacturing resources (DTs) will be integrated into CPPS. Finally, this paper describes a case of information modeling for blisk machining and demonstrates the modeling approach in real-life scenarios for support manufacturing resource sharing via DT. Furthermore, the conclusion and further work is briefly summarized.

**Keywords** Information modeling · Production system · Digital twin · AutomationML · Intelligent manufacturing

## 1 Introduction

More and more manufacturing enterprises are under pressure to reduce costs and respond rapidly to the changing marketing environment, such as shorter product lifecycle [1], stochastic orders, individualized product [2, 3], and the unplanned disruptive manufacturing process [4]. To meet these challenges, the rapid integration of manufacturing resources and the real-time decision-making at change scales in a shop floor and even globally have become an urgent issue [5]. For these influences, there have been many efforts devoted to developing cyber-physical production system (CPPS) [6]. Both production specialization and networked manufacturing may impose requirement for CPPS shifting to the dynamic manufacturing environment that focuses on the real-time decision-making. Recent advancement of information and communications technologies (ICTs) provides key supporting technologies to CPPS, such as agent, radio frequency identification (RFID), edge computing, artificial intelligence, machine learning, and mobile internet. Since ICTs have been employed in the manufacturing industry, there are some challenges for interconnection and interaction between physical resources and virtual ones. These challenges can be classified as the following:

- Self-description and self-adaption of manufacturing cell (MC). MC may be machines, software, and devices (such as computer numerical control machine tools, 3D printers, automated guided vehicle, radio frequency identification,

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industrial robot/robotics, and industrial software). Some simple devices can be integrated for one complex MC. For example, a flexible machining unit may be composed of a lathe, a machining center, and a robot. The self-description can provide the geometric information and the functional specifications of physical MC, which will be a digital twin of the corresponding MC in the virtual space [7]. Firstly, the MC capacity should be described accurately and encapsulated. Standard interface access to MC should be provided. There need to be automatic discovery and registration of MC. Self-adaption includes the combination and decomposition of tasks, the dynamic matching between tasks and resources, and the capability evaluation of MC. [6].

- Self-awareness and self-tracking of manufacturing resources. Along with the miniaturization and price decline of sensors and networks [8], more and more manufacturing resources and process will be monitored and remotely controlled. For example, various sensors can be used for monitoring the rapid ramp-up and downscale of manufacturing resources, such as pressure sensor, temperature sensor, and speed sensor. For self-tracking, there are global positioning system (GPS) for outdoor position, ultra-wideband (UWB) for indoor position, and RFID for automatic contactless identification and tracking.
- Demand for frequent machine-to-machine connectivity, complex human-to-machine interaction, and various standard diffusion of industrial communication interfaces. This is a trend of automatic interaction among machines and human beings in shop floors. For example, the computer numerical control (CNC) system can provide the automatic error compensation according to the position measurement from online measuring system. Operators can monitor the real-time equipment operational status by industrial mobile phone or iPad. When fault occurs, the production system adjusts process automatically or with human intervention.
- Towards "manufacturing as a service" based on cloud computing [9] and cyber-physical system (CPS) [10, 11]. With the development of agent and industrial internet technology, the local manufacturing resources can be encapsulated as services that are shared even globally. Manufacturing services can overcome the distance and heterogeneities of physical resources. The different types of manufacturing resources may complete the same task, even though the resources were in different locations, using different CNC systems, and owned by different manufacturing service providers (MSPs). For example, both a CNC lathe with FANUC system and a machining center with SIEMENS system can process typical rotational parts, but the cost of the latter may be higher than that of the former. The interaction and integration of manufacturing resources should be realized among various services [12]. Manufacturing services support on-demand use and dynamic reconfiguration [13], since these services are deployed in the cyber space of CPPS.
- Intelligent decision-making for disruptive events and demand fluctuations. Manufacturing resources (e.g., machines and human beings) will generate a huge amount of data in the CPPS, such as production static/historical data and dynamic/real-time data. Data analysis should be developed for intelligent decision-making. Self-organizing production system should be supported by not only production data but also data-driven operational knowledge, especially for the production process monitoring, the scheduling optimization, and the fault diagnosis and prediction. These methods of decision-making (e.g., information fusion) need the descriptive model, the prognostic model, the predictive model, and the prescriptive model, which are stored in the cyber space of CPPS.

Machine-to-machine connectivity and human-to-machine interaction are the first step of developing CPPS, allowing different format data access and sharing for different applications. In essence, it can be considered that the technological basis of CPPS roots back to IoTs [14]. Sensors, RFID and embed electronics are used for the perception of manufacturing resources. While the perceptual information is uploaded to the cloud, the production scheduling information is downloaded to local resources from the cloud. It is essentially the collection and exchange of data through wired or wireless network, such as equipment status, production schedule, and production environment. Data at different stages of production, ranging from raw materials, machines' operations, facility logistics, and even human operators, should be collected and processed [15]. However, while new machines, sensors, communications network, etc. are designed and prepared for these new features, current production systems are limited or cannot integrate different format data. How to improve the resource-integration efficiency is a key of CPPS research.

CPS is an important concept in the era of Industry 4.0. More and more people focus on how to apply CPS into the manufacturing industry. Overall, the benefits from the application of CPS in production include (1) production processes, (2) product customization, (3) production efficiency, and (4) human-machine interaction [16, 17]. CPS can support the seamless communication among manufacturing resources. More importantly, the relationship among physical resources will be mapped in the cyber space for monitoring, optimization, prediction, and so on. There are some approach to data collection and analysis for CPS. The cyber space can control certain physical equipment, while the control instructions come from operators or artificial intelligence [18]. However, to realize the application of CPS in the manufacturing industry, the real-time and efficient interaction will be essential between the physical space and the virtual space [19].

Digital twin is an effective way of technology and method for solving the above problems [20]. Digital twin is considered to be the collaborating computational entities, a core component of CPS. Digital twin represents the first step for realizing CPS, following the data analysis, and the optimization of production process. The advantages introducing the digital twin in the production system significantly contribute to the production transparence and to near real-time optimization [21], which is the typical feature of intelligent manufacturing. Through DT, a real-time relation can be built between physical manufacturing resource and corresponding virtual one. Through CPS, the data generated from the physical manufacturing resource can be stored in the virtual world, and then the result of simulation, optimization, and prediction of data in the virtual world will be delivered to the physical manufacturing resources, as shown in Fig. 1. However, there exist three main facts: (i) since there is frequent interaction and communication among various manufacturing resource in CPPS, different data formats are an obstacle to fulfill interoperability among various physical manufacturing resources; (ii) there is a lack of standardized data format for interoperability between physical manufacturing resource and their virtual one; (iii) virtual manufacturing resources (e.g., industrial software) usually use specific format of data (e.g., images, documents, videos), leading to hard information interaction throughout the product lifecycle.

The need for a standardized information model has been getting more and more attention. As is known to us, some specifications have existed for information modeling. However, there was lack of a unified format for the description and exchange of production information. Although both researchers and engineers have always focused on the standardization of information, the problem still exists in the manufacturing industry. The more is the type and quantity of self-aware machines, the lower is the reliability of the information exchange. That is because there is lack of unified exchange standard, which is important to map information [22]. Uhlemanna et al. concluded that the first step of realization of CPPS is to develop digital twin of the corresponding manufacturing resource, but that standardization of data acquisitions has not yet been achieved, which hinders the development and application of digital twin. Following the requirements of data acquisition standardization, the scalability and usability of the information model are considered [21]. The new information model is required to support the data acquisition and information fusion of the virtual and real manufacturing resource, so that the CPPS can be feasible and robust enough in a complex and changeable production environment. In the context of CPPS, the novel reference architectures of information models is needed to support the integration of real manufacturing resource and the corresponding DT, while it needs to support the specific interaction between the real manufacturing resource and the corresponding DT, and the context-adaptive resource optimization algorithms [23] for shop floor are needed.

Based on our previous work [24], this paper focuses on developing a novel information modeling approach for CPPS based on DT and AutomationML. The goal of this following paper is to describe how to solve the information exchange and manufacturing resource sharing according to the abovementioned challenges of CPPS. The content of this paper is to present a novel architecture and an information modeling approach in order to integrate and share various manufacturing resources. DT will be virtual representations of real things (e.g., manufacturing devices) in the context of CPPS. DT includes production models of subsystems and production data with different formats. The problem is how to design the architecture of CPPS that can support seamless connection among resources and a semantic information model. The information model should allow different applications to access to the real-time synchronized data. This paper is organized as follows. Section 2 presents the literature review that explains the theoretical foundation and related work of CPPS and DT, and thus points out the existing challenges and limitations of current research. A generic architecture of CPPS based on DT is proposed in section 3. Meanwhile, a case of expert fault diagnose for aircraft engine is given based on information fusion in the proposed architecture. Section 4 introduces the concept of manufacturing service and the service-oriented CPPS, and thus the information modeling approach based on AutomationML is explained for the service-oriented CPPS in detail. Finally, this paper demonstrates the scenario

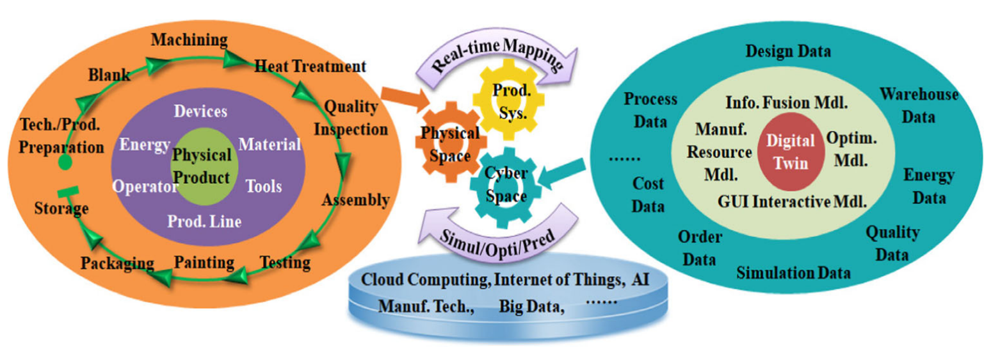



**Fig. 1** Physical space and virtual space in CPPS

analysis of the proposed approach of information modeling, and thus an industrial case study of the blisk manufacturing plant is illustrated within the platform of CPPS via DT to validate the approach of information modeling.

## 2 Literature review

This section gives a systematic literature review and some industrial best cases of CPPS and DT.

### 2.1 Cyber-physical production system

Firstly, some former significant developments related to CPPS have be enumerated, despite with different names. For example, intelligent manufacturing system [25] responds the changes in the dynamic manufacturing environment independently; biological manufacturing system [26, 27] copes with biologically inspired ideas for the shop floor level; reconfigurable manufacturing system [28], digital factory [29–32], holonic (agent-based) manufacturing system (HMS) [33–38]. In this paper, Agent-based approaches (plug-and-produce) [39] and cloud computing [40–45] give us the idea of developing CPPS.

CPPS is the specific application of CPS in the manufacturing field, which has been researched for a few years [18]. First definition of CPS can be found at the workshop supported by the American National Science Foundation in 2006 [46]. Since Germany proposed Industry 4.0 in 2011, this concept has attracted attention increased by 40% in average per year [17]. The widely accepted definition of CPPS is that systems of systems of autonomous and cooperative elements connecting with each other in situation dependent ways, on and across all levels of production, from processes through machines up to production and logistics networks, enhancing decision-making processes in real time, response to unforeseen conditions, and evolution along time. The classical definition of CPPS has been widely accepted in academia and industry for a few years, since it underlines the resource connectivity and the intelligent decision-making [18]. However, the effective information interaction is missing in the context of CPPS. Notions (e.g., digital twin) are not presented, which are used for real-time monitoring, optimization simulation, and intelligent forecasting [17].

Rojas and Rauch [47] firstly gave a systematic literature review of CPPS and then presented the CPPS control system architecture for realizing intelligent manufacturing. Woo et al. [48] introduced a smart manufacturing towards manufacturing platform, which advanced the agent-based framework system. Zhuang et al. [49] proposed a framework of CPPS based on DT for assembly shop floors. In [50], a concept based on gateway and server was presented to integrate production subsystems into CPPS. Projects such as IMC-AESOP [10] considered that the cloud technology would be employed in the future industrial systems [17]. Monostori et al. [51] introduced a 5C architecture, which consists of five levels and illustrates how to develop CPPS, as is shown in Fig. 2 [52]. Monostori et al. [52] underlined that the architecture of CPPS should be different from the traditional automation pyramid, while the higher level of functional components incorporated cloud computational capabilities, big data analytic, and intelligent decision-making that were the core components in the cyber space. Botond et al. [53] presented that a virtual factory framework could provide a virtual environment, which integrated various resources, shared the manufacturing information, and mined production knowledge, while supporting the intelligent production management along the product's lifecycles. The well-known ANSI/ISA-95 has been considered as a standard of information exchange, where the service oriented architecture (SoA) is employed in the manufacturing field [54]. However, the ANSI/ISA-95 cannot support the placement modeling and the shape modeling of physical resource [22]. Ma at al. [55] presented the architecture of CPS-enabled production system for energy-intensive manufacturing industries to support the strategy of cleaner production. Monostori et al. proposed the combination of AutomationML and Object Linking and Embedding for Process Control - Unified Architecture (OPC-UA) as information exchange format in the context of CPPS [52]. Terkaj and Urgo [22] presented an ontology-based information model for supporting the development and evaluation of production systems. The OPC-UA and manufacturing service bus have already been proposed for the communication level of CPPS [56, 57], but their integration of resources remains to be studied since lacking of unified format of manufacturing resource information. Zhang et al. [58] proposed a three-layer framework for smart production-logistics system, which can implement the modeling of resources and the self-organizing configuration. Several standards and protocols of wired and wireless communication technologies, such as TCP/IP, RS-232C, ISA100.11a, and

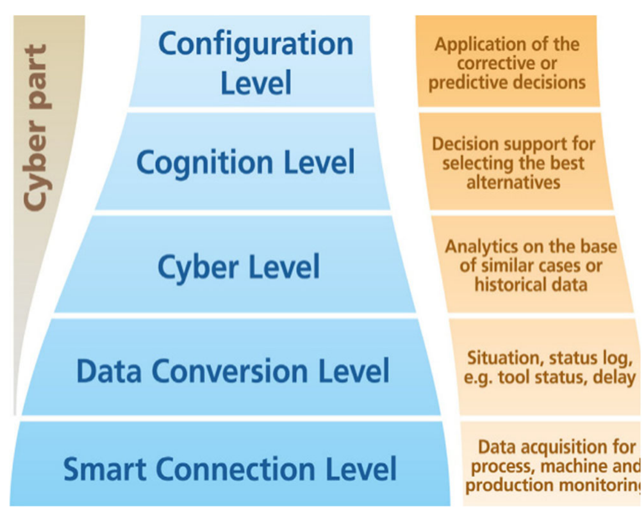



**Fig. 2** 5C architecture for implementation of CPPS

IEEE 802.11e, can support the data communication among manufacturing resource or between manufacturing resource and cloud servers. The above research and practices are valuable to CPPS. Our proposed architecture focuses on how to information fusion and information unified modeling, while Zhang's architecture focuses on self-organizing configuration. Ye and Hong [59] developed a refined architecture of CPPS including enterprise layer, information layer, communication layer, and field layer, which referenced the RAMI 4.0 architecture. Compared with the architecture proposed by Ye and Hong, this paper introduces digital twin in the information layer (corresponding to the virtual layer in this paper), which is especially helpful to improve data management mechanism in order to support the application services in the upper layer.

### 2.2 Digital twin

The real manufacturing resource can be represented in the virtual space, while the virtual space can be updated in near real time using data from sensors in the real space (e.g., things) [60]. DT is an essential part of Industry 4.0 to promote the production optimization and performance prediction. The definition of DT can be referred to literature [61], which concludes the related literature from 2012 to 2016. DT comprises the next wave in the digitization of shop floor [62]. As shown in Fig. 3 [63], DT has been widely applied in the different stages of products, such as design, simulation, testing, production, and prognostics and diagnostic. Lee et al. [64] considered that DT represented the virtual counterpart of manufacturing resources, besides the product in the shop floor. Uhlemanna et al. [65] presented a learning factory concept, which introduced the benefits of DT applied in the production system. For example, DT can enhance transparency and promote potentials for optimization of production systems. Coronado et al. [60] proposed a new

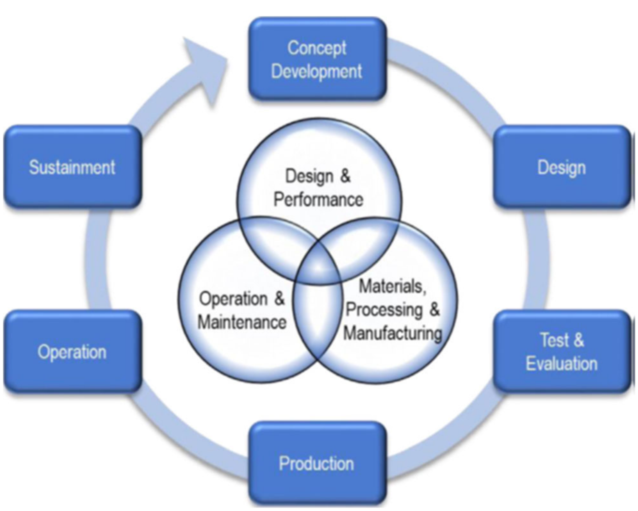



**Fig. 3** Application scenarios of DT in smart manufacturing

manufacturing execution system that supported the management in the shop floor, which collected production data using the MTConnect protocol. Talkhestani et al. [20] presented an engineering DT that was developed in a PLM IT platform based on model integration using anchor-point method in order to realize the exchange of systematical mechanical data between the virtual space and the physical space.

## 3 Generic architecture of CPPS based on DT

In order to solve the challenges mentioned in section 1, this section mainly applies the concept of DT to build the architecture of CPPS. In addition to ICT, advanced manufacturing technologies are constantly appearing. Therefore, the architecture of CPPS should be an effective and open communication one, allowing the dynamic integration of various manufacturing resources and their frequent interaction operations. The proposed architecture of CPPS based on DT is as depicted in Fig. 4, which should support the following aspects:

- The meta data model which structures data generated from various production subsystems, such as product lifecycle management (PLM), enterprise resource planning (ERP), manufacturing execution system (MES), and advanced planning and scheduling (APS), in order to ensure the continuity and consistency of data;
- The physical layer based on IoTs which can support the seamless interaction of the physical space to the virtual space, to achieve real-time monitoring and optimization with manufacturing big data;
- Configuration data which is predefined and static to describe the physical product and manufacturing resources in shop floors;
- Runtime data which is dynamic and abundant to describe real-time status of the manufacturing resource and process, such as the operation of the machine and the inventory data;
- Model data, which includes model-based definition (MBD) model of product, information fusion model, and graphical user interface interactive model.

### 3.1 Components and functions

(1). Physical layer:

The manufacturing cell agent (MCA) can encapsulate specific descriptions and functions of manufacturing resources. These MCAs are the basic units in the physical layer. CPPS reconfigures these MCAs in the virtual space for responding to the change of dynamic production environment. Meanwhile, MCA has the function of local self-organization, besides

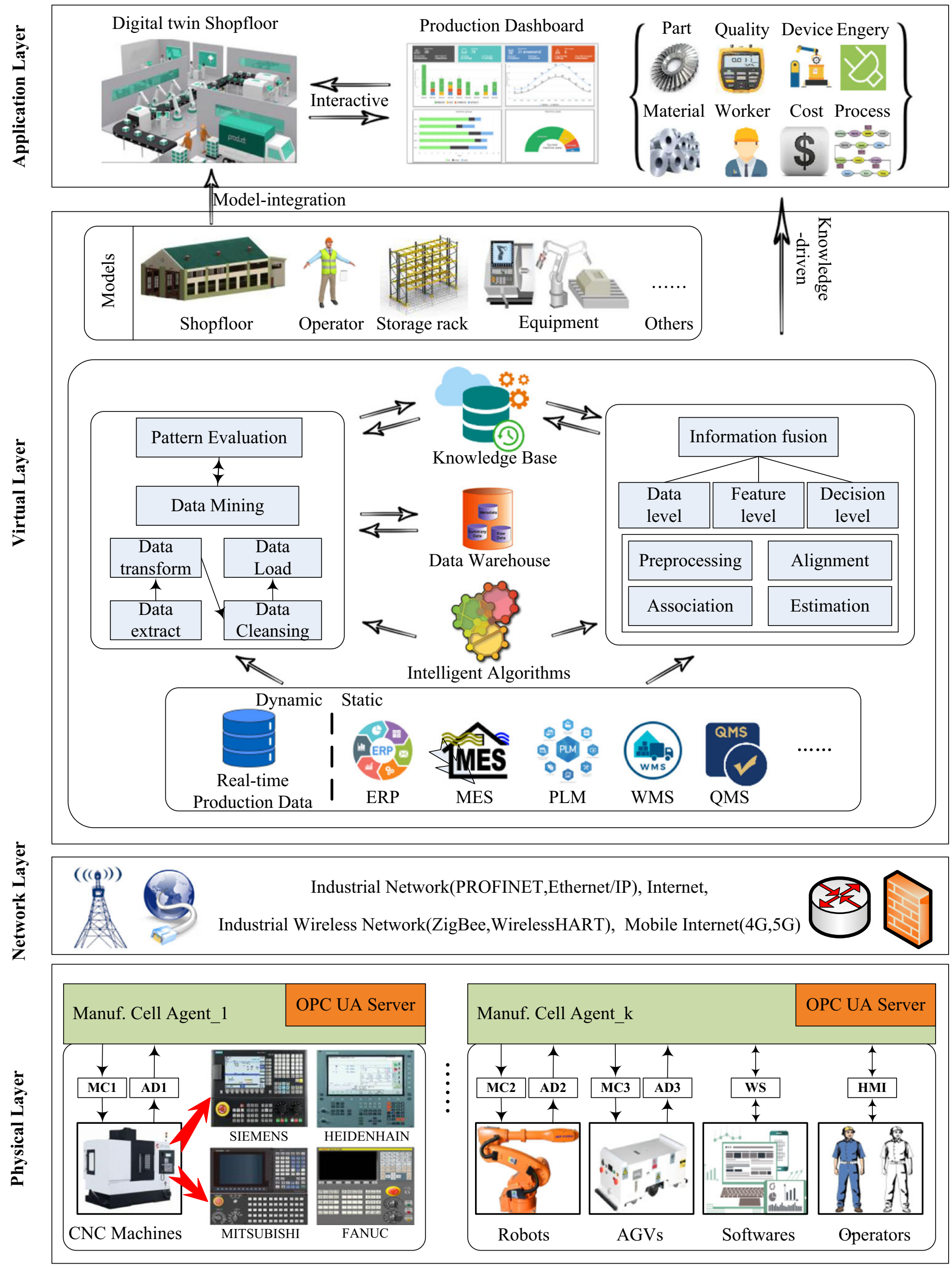



**Fig. 4** Architecture of CPPS based on DT

accepting the scheduling instruction from the upper layer of CPPS. For example, in order to receive a batch of rush orders offline, MCA can suspend the sharing of manufacturing resource online.

As regards to the specific implementation, MCA can be developed based on the configuration software and the B/S architecture, which will be deployed on a local/remote server rapidly at low cost. MCA can support most major CNC systems (e.g., FANUC, SIEMENS, SYNTEC, MITSUBIISHI, BROTHER, MAZAK, HEIDENHAIN, and HAAS), while MCA can also support the data acquisition and communication of PLC. In this paper, the OPC-UA server is built in MCA, which has the communication gateway of industrial IoTs and can publish the data of connected manufacturing resources to the cloud servers. In this paper, the OPC-UA server will be used to convert all kinds of protocols in the field of industrial communication (e.g., Modbus communication protocol and BACnet communication protocol) into a unified format (e.g., AutomationML).

The micro-controller (MC) executes instructions. The MC products can be available in the market, such as Intel, ATMEL, Philips, Dallas, Siemens, and Winbond. The production data is very important to CPPS, which can be collected by the data acquisition device (DA). According to the acquisition frequency of DA, the production data can be divided into the following ways: continuous acquisition, periodic acquisition, and ready-to-run acquisition. The DA products can be available cheaply, such as data acquisition cards provided by National Instruments, Advantech, Schneider. Industrial software can be shared in the form of services. For example, the MSP can accept orders online, and then design and compute offline and submit the final result to the manufacturing service consumer (MSC). Another way is that MSC can submit the task online and design on their own through the software interfaces. The human-machine interaction (HMI) can be realized through intelligent wearable devices, such as HONEYWELL's skills insight and MIT's Safety++.

(2). Network layer:

The network infrastructure is located in this layer. A large amount of data that is collected from the physical layer will be transmitted and saved in the virtual layer, through the standard network protocols. These protocols, such as Modbus, BACnet, Profinet, RS-485, TCP/UDP, and Devicenet, can be selected as the configuration of equipment according to the specific requirement. For example, ABB robots select Devicenet as the basic configuration and Profinet as optional configuration. The selection principle is reliable, low cost, and easy to deploy. A key point of current research is how to converge the heterogeneous networks among various subsystems, since there are many heterogeneous and multi-source of manufacturing resources. OPC-UA can provide a way for solving interoperability and standardization, which is cross-platform, more robust, and secure.

(3). Virtual layer:

This layer includes various data bases, knowledge base, model base and data mining, and information fusion, which provide production data and knowledge to various applications in the upper layer. This layer is very important to develop DT for CPPS.

For the real-time production data and relatively static data (e.g., ERP, MES, WMS, PLM), these data should be loaded and stored in the data warehouse, after data prepossessing (extracting, transforming, cleaning). The data modeling for warehouse includes business model, domain model, logical model, and physical model. Modeling methods include paradigm modeling, dimensional modeling, and entity mode. Multiple source data will be integrated into a single database using the unified data model. Only one query engine can be used for data mining. Then the algorithm will be selected for data mining, and the pattern will be explained and evaluated, which will be imported in the knowledge base. The methods of data mining have Decision Tree, Support Vector Machine, Bayes Classification, Genetic Algorithm, Fuzzy Set, etc.

Although the real-time data related to equipment performance and operation condition can be collected through MCAs in the physical layer, various data appear to be uncertain, inaccurate, and incomplete. Because there are complex operating condition and multiple factors for equipment in CPPS, there exist non-linear mapping relationship among detection signals, fault features, and fault source. Meanwhile, the requirements of volume and processing speed for multi-form data have also increased. Among the multi-source information fusion technology, the fusion method based on database is suggested for CPPS, while employing patterns in the knowledge base. The results of information fusion will provide the basis for fault diagnosis or decisions, such as walking, obstacle avoidance and objects grabbing of robots, expert fault diagnosis for aircraft engine, and CNC machine tools. The key technology for information fusion is as follows: Dempster-Shafer (D-S) evidence theory, cluster analysis, fuzzy theory, neural network, rough set, etc.

Digital twin is an important part of CPPS, which is built on the 3D digital model (e.g., production line, operators, equipment, tools); the data; and knowledge to simulate their behaviors [66]. Developing various models is an important step to build DT in CPPS. These models can be divided into four kinds: manufacturing resource model (MRM), information fusion model (IFM), graphical user interface interactive model (GUIIM), and behavior and rule model (BRM) [24]. MRM includes three kinds of information: ① product processing technology, such as process route, operation, cutting parameters, processing time, fixture, cutting tool. ② Geometric information of manufacturing resources, such as dimensions, material, shape.③ Attributes of manufacturing resources, such as function description, energy saving, cost, machining accuracy, productivity. 3D models of physical manufacturing resources can be built using 3D MAX, Rhinoceros, Creo, NX, Solidworks, and so on, which transform models into FBX format. GUIIM supports the interaction and feedback with users. GUIIM shows the real-time parameters of manufacturing resource, when mouse focuses on its model. These 3D models will be driven by the rules and reasoning in the knowledge base. For example, if some equipment broken down in production line, its 3D model will show red fault signal in CPPS. According to the predefined rule, the model of whole production line stops, while the physical production line also stops. BRM refers to the behavior and rule of manufacturing resources in the shop floor. The behavior includes activities of manufacturing resources in the shop floor, such as cutting of machine tool, gripping of robots, and clamping of fixture. The rule is to describe the knowledge of production control and scheduling, which is used for evaluating, optimizing, and predicting the behavior. The shop floor rules include the process route of product, the priority of production orders, part shortage management rules, quality management rules, and energy consumption rules. More and more rules should be obtained automatically by information fusion method. Therefore, information fusion is very important to realize the digital twin, which is a key point to the proposed architecture. Combining with the previous research of our research group, this paper proposed a method of information fusion, and then this method was tested for aircraft engine expert fault diagnose in section 3.2.

(4). Application layer:

This layer is oriented to product design companies, manufacturing companies, suppliers, and customers. The application towards CPPS includes smart production control, intelligent scheduling, intelligent quality management, intelligent expert fault diagnose, and intelligent logistic. These applications will be provided to users through 3D real-time dynamic models or the production dashboard. The 3D real-time dynamic models can support the intuitionist and friendly interaction for human-to-machine, while the production dashboard can provide more detailed information through charts, such as operators, equipment, quality, cost, and energy consumption.

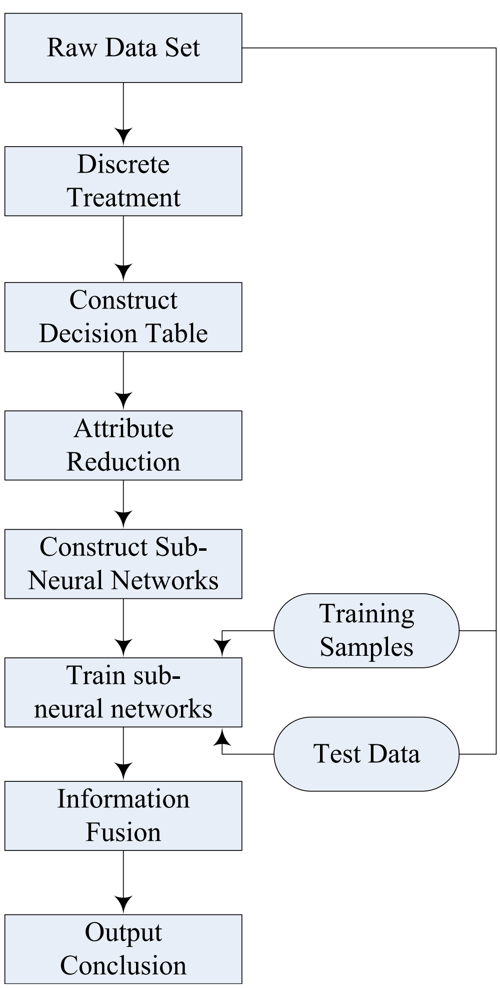



**Fig. 5** Flowchart of EFDAE

### 3.2 Case study of architecture

According to the proposed architecture, a case study of expert fault diagnose for aircraft engine (EFDAE) is given in this section. The flowchart of EFDAE is shown in Fig. 5. In the early stage of fault diagnose, a great deal of the spectrometric oil analysis (SOA) data of aircraft engine will be collected as training samples under the two conditions (abnormal and wear), which includes the concentration of seven elements $\{Fe, Al, Cu, Cr, Ag, Ti, Mg\}$. The raw data of concentration is shown in Table 1, where ID is the index of oil sample, F represents the model of fault, and "0" and "1" represent the abnormal condition and the wear condition, respectively. The SOA data of a certain kind of aircraft engine can be transformed and collected by the AD module as test data, and then will be updated to the virtual layer through the network layer. In this section, the SOA data will be analyzed based on the proposed method, which is used for data mining and information fusion located in the virtual layer of CPPS.

Let the error bound of incompatibility $\beta = 0.25$ and the consistency measure of decision table $\alpha = 10^{-7}$, and then the incompatibility estimation of each element $\widetilde{\alpha} = \sqrt[7]{\alpha} = 0.1$.

**Table 1** Raw data for spectrometric oil analysis

| ID | Concentration of element | | | | | | | F |
|---|---|---|---|---|---|---|---|---|
| | Fe | Al | Cu | Cr | Ag | Ti | Mg | |
| 1 | 0.5 | 0 | 0.3 | 0 | 0.1 | 0.5 | 2 | 0 |
| 2 | 1.6 | 0 | 0.6 | 0 | 0.1 | 0.6 | 2.9 | 0 |
| 3 | 2.6 | 0 | 0.9 | 0.2 | 0.2 | 0.7 | 3.5 | 0 |
| 4 | 2.3 | 0 | 0.6 | 0.1 | 0.2 | 0.5 | 4.8 | 0 |
| 5 | 2.6 | 0 | 0.6 | 0.2 | 0.2 | 0.6 | 4.4 | 0 |
| 6 | 3.2 | 0 | 0.7 | 0.3 | 0.2 | 0.7 | 5.1 | 0 |
| 7 | 4.8 | 0 | 1.5 | 0.2 | 0.1 | 1 | 6.1 | 0 |
| 8 | 15.6 | 0.5 | 2.4 | 1.4 | 0.5 | 1.1 | 7.2 | 1 |
| 9 | 1.6 | 0 | 0.7 | 0 | 0 | 0.6 | 3.3 | 0 |
| 10 | 1.6 | 0 | 0.8 | 0 | 0.1 | 0.8 | 3.4 | 0 |
| 11 | 1.4 | 0 | 0.8 | 0.1 | 0.2 | 0.8 | 3.2 | 0 |
| 12 | 1.6 | 0 | 0.6 | 0.4 | 0.2 | 0.7 | 3 | 0 |
| 13 | 1.5 | 0 | 0.6 | 0.1 | 0.2 | 0.5 | 3.2 | 0 |
| 14 | 1.5 | 0 | 0.5 | 0.1 | 0.2 | 0.8 | 3.6 | 0 |
| 15 | 8.8 | 0 | 1.9 | 0.4 | 0.5 | 1.4 | 4.7 | 1 |
| 16 | 8.1 | 0.7 | 1.1 | 0.4 | 0.8 | 1.2 | 8.4 | 1 |
| 17 | 32.3 | 4.7 | 5.8 | 6.2 | 2.1 | 10.5 | 1.4 | 1 |
| 18 | 23.9 | 1.8 | 9.8 | 1.1 | 1.8 | 1.9 | 9.3 | 1 |
| 19 | 19.2 | 0.6 | 1.8 | 1.5 | 0.4 | 1.3 | 5.6 | 1 |
| 20 | 11.7 | 0.4 | 4.7 | 0.7 | 0.9 | 1.7 | 8.4 | 1 |

**Table 2** The importance degree of elements

| Element | Fe | Al | Cu | Cr | Ag | Ti | Mg |
|---|---|---|---|---|---|---|---|
| Importance degree | 1.69 | 1.13 | 1.37 | 1.12 | 1.50 | 0.94 | 1.22 |
| Sorting | 1 | 5 | 3 | 6 | 2 | 7 | 4 |

Therefore, the discreted incompatibility of each element $\alpha_i$ should satisfy the requirement of $|\alpha_i\tilde{\alpha}| < \beta$. Firstly, accurate the importance degree of every element, according to $SGF(A) = \frac{\max(mean(A_i)-\min(mean(A_i))}{\sigma}$, where $\sigma$is the standard deviation of sample A. Then the result of the importance degree is shown in Table 2. The artificial neural network (ANN) is used as classifier, and let the initial number of clusters 2. The concentration of seven elements should be discreted into 2 groups, which is shown in Table 3. Secondly, accurate the incompatibility of every element $\alpha_i = \frac{Card\left(\widetilde{A_i}\right)}{Card(U)}$ (Table 4) and the incompatibility of decision table $\alpha = \prod_{i=1}^{m} \alpha_i$.

The input values of ANN are classified and sorted according to the classification of the output. The discrete breakpoints of input values are set as average values between maximum of class $i$ and minimum of class $i+1$, whose result is shown in Table 5.

**Table 3** The element concentration

| ID | Fe | Al | Cu | Cr | Ag | Ti | Mg | F |
|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| 2 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| 3 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| 4 | 1 | 1 | 1 | 1 | 1 | 1 | 2 | 1 |
| 5 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| 6 | 1 | 1 | 1 | 1 | 1 | 1 | 2 | 1 |
| 7 | 1 | 1 | 1 | 1 | 1 | 1 | 2 | 1 |
| 8 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 |
| 9 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| 10 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| 11 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| 12 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| 13 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| 14 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| 15 | 2 | 1 | 1 | 1 | 2 | 1 | 2 | 2 |
| 16 | 2 | 2 | 1 | 1 | 2 | 1 | 2 | 2 |
| 17 | 2 | 2 | 2 | 2 | 2 | 2 | 1 | 2 |
| 18 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 |
| 19 | 2 | 2 | 1 | 2 | 1 | 1 | 2 | 2 |
| 20 | 2 | 1 | 2 | 1 | 2 | 2 | 2 | 2 |

**Table 4** The incompatibility of elements

| Element | Fe | Al | Cu | Cr | Ag | Ti | Mg |
|---|---|---|---|---|---|---|---|
| Incompatibility | 1 | 5 | 3 | 6 | 2 | 7 | 4 |

The attribute reduction method $C_T(i,j) = \begin{cases} \{\alpha_k | \alpha_k \in P \wedge \alpha_k(x_i) \neq \alpha_k(x_j)\} & T(x_i) \neq T(x_j) \\ 0 & T(x_i) = T(x_j) \end{cases}$ (where $i, j = 1, 2, \cdots, n$) is employed based on discernibility matrix in this paper. The result of attribute reduction is $\{Fe\}$, $\{Al, Ag\}$, and $\{Cr, Ag\}$for Table 3. As you can see, the attribute set $\{Fe\}$ is uncorrelated to two others $\{Al, Ag\}$, $\{Cr, Ag\}$. According to the construction principle of ANN, two sub-neural networks (SNNs) can be constructed with the sets $\{\{Fe\}, \{Al, Ag\}\}$ and $\{\{Fe\}, \{Cr, Ag\}\}$ in this case, respectively. The information that is entered includes the content of element *Fe* for SNN 1 and those of *Al* and *Ag* for SNN 2. Take the spectrometric oil analysis data of aircraft engine for example, the concentrations of seven elements {*Fe*, *Al*, *Cu*, *Cr*, *Ag*, *Ti*, *Mg*} are $\{15.8, 0.4, 2.4, 1.3, 0.5, 1.1, 7.2\}$ (unit: mg/L) respectively. Then using the fault diagnose model, the diagnosis result of SNN 1 is 0.935 (wear possibility), while that of SNN 2 is 0.924. These diagnosis results are fused based on Dempster-Shafer (DS) evidence theory.

Let the set function $f: 2^{\Theta} \to [0, 1]$, satisfying $f(\varnothing) = 0$, $\sum_{S \subset \Theta} f(S) = 1$, where $f$ refers to the valuation of basic probability assignments (BPA) and $f(S)$ refers to the support degree for sample $S$.

The combination rule is as follows:

$$\begin{cases} f(\varnothing) = 0 \\ f(S) = \sum_{S_i \cap S_j \cap S_l \cdots = S} f_1(S_i) \cdot f_2(S_j) \cdot f_3(S_l) \cdots + k \cdot q(S) \\ k = \sum_{S_i \cap S_j \cap S_l \cdots = \varnothing} f_1(S_i) \cdot f_2(S_j) \cdot f_3(S_l) \cdots \end{cases}$$

where $q(S) = \frac{1}{n} \sum_{1 \le i \le n} f_i(S)$ refers to the average support

**Table 5** Discrete interval of element concentration

| Element | Discrete interval | |
|---|---|---|
| | 1 | 2 |
| Fe | (0, 6.45) | [6.45, +∞] |
| Al | (0, 0.45) | [0.45, +∞] |
| Cu | (0, 2.15) | [2.15, +∞] |
| Cr | (0, 0.90) | [0.90, +∞] |
| Ag | (0, 0.45) | [0.45, +∞] |
| Ti | (0, 1.55) | [1.55, +∞] |
| Mg | (0, 4.55) | [4.55, +∞] |

degree for sample $S$, $k$ is a measure of the amount of conflict between the two mass sets.

Calculate $q(S) = \frac{1}{2}(0.935 + 0.924) = 0.9295$,

$$k = 0.935 \times (1{-}0.924) + 0.924 \times (1{-}0.935) \ = 0.1311,$$

$$f(S) = 0.935 \times 0.924 + 0.1311 \times 0.9295 = 0.986$$

Thus, the conclusion can be drawn that the wear possibility of aero-engine is 0.986, namely the aero-engine should be under wear condition. Finally, the fault position and condition is shown by CPPS in the application layer.

## 4 Information modeling approach for CPPS

### 4.1 Service-oriented CPPS

Under the situation of shorter product life cycle and more specialized division of production, manufacturing services will be a trend of development in the manufacturing industry [67]. In the form of services, some manufacturing resources can be better shared in a plug-and-play manner [68]. In view of the concept of everything-as-a-service (XaaS), services could fully release the potential of digital twin [69]. DT will be an effective way to realize services in the CPPS.

According to the proposed architecture in section 3.1, these physical manufacturing resources should be encapsulated as manufacturing services by MCA. MCA can publish these manufacturing services and get the process instructions from the application layer. Meanwhile, MCA will send the real-time data of manufacturing progress to digital twin in the virtual layer. Manufacturing service consumers (end users) can query, control, and optimize the manufacturing progress through digital twin in virtual layer. By employing MCA, some manufacturing resources are not required to be located in one factory. Through digital twin, the production process will be transparent to both MSP and MSC. As shown in Fig. 6, there are data acquisition (DA) and mic-control (MC) between MCA and physical resource. MCA is responsible to publish manufacturing services and receive the instruction. MSC can invoke various manufacturing services for complex manufacturing tasks (layer 1 in Fig. 7). In this paper, the digital twin in CPPS can be viewed as combination of manufacturing services, manufacturing big data, and virtual models.

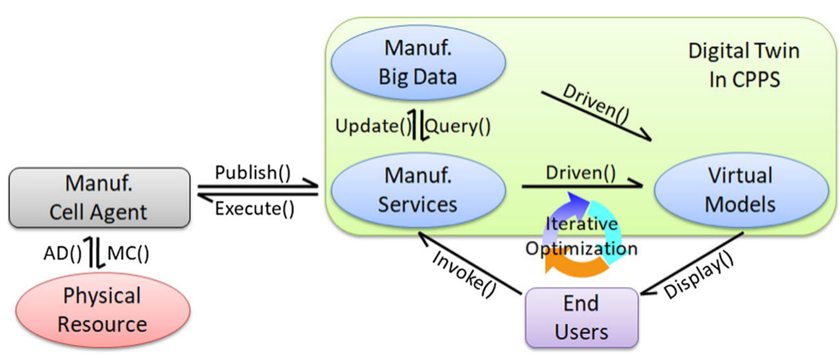
In Fig. 7, there need many tasks (processes) for the blisk machining in layer 1. Various manufacturing services (e.g., milling, drilling, grinding, and measuring) are provided by many MCAs in layer 2. These manufacturing services can be discovered and combined to perform more complex tasks (like *Task_co1* in Fig. 7) through CPPS. For MS_2, there are three MCAs which can provide the required services or better ones, while there is only one MCA which can provide the required services (MS_n). There are attributes in layer 4 and parameters in layer 5. It should be noted that for the same MS, attributes can be the same regardless of MSP, but the values of parameter may be different depending on the actual MSP. Since many tasks can be accomplished on the same equipment in the plant, tasks can be combined in layer 1. For example, $Task\_2$ and $Task\_3$ can be combined into $Task\_co1$ through CPPS. Finally, the appropriate MCAs are found and matched by CPPS according to tasks; ten MCA performs specific processing tasks.

In this paper, the purpose of information modeling is to formally describe real manufacturing resources in the CPPS. According to the proposed architecture of CPPS, the information modeling will be automatically finished by MCAs. Beyond product data, MCAs integrate the relevant information like logical behavior, kinematics, and motion and thus represent the production behavior and process completely. The aim of MCAs is the simple and complete exchange of production data and functionality among heterogeneous systems. The meta-model of MCA is open and shared. The MCA model serves as a template for creating instances by the physical MSP like grinder, lathe, NC machining center, and industrial software. Therefore, it is particularly suitable for users who are difficult to establish DT without professional knowledge [69].

### 4.2 Information modeling of CPPS

This section focuses on information modeling for CPPS. In the past, the approaches of information modeling have been

**Fig. 6** Flowchart of service-oriented CPPS



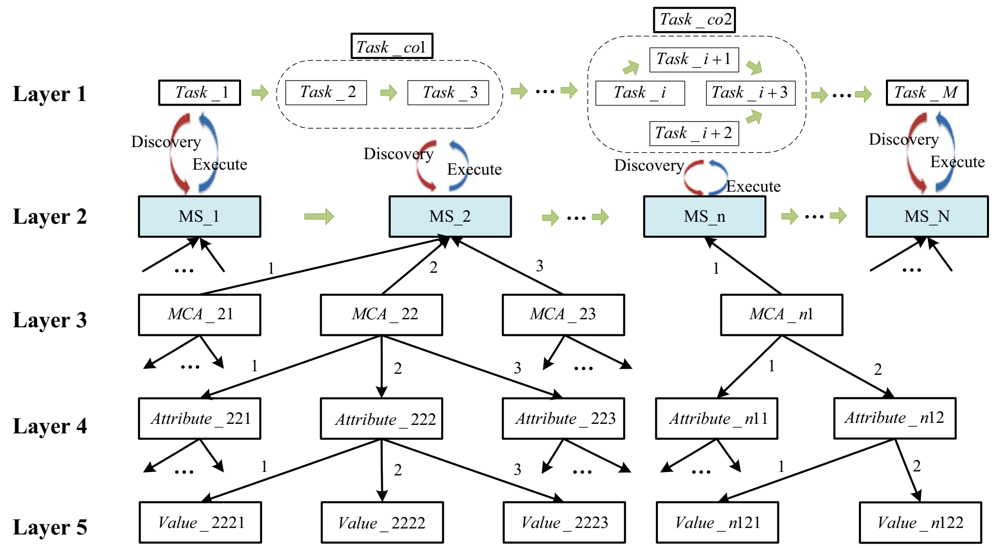



**Fig. 7** Discovery and match in CPPS (MS, manufacturing service)

presented [70], while the detailed various methods were shown in Table 6, such as STEP (standard for the exchange of product model data), XML (extensible markup language), ontology, and AutomationML (automation makeup language) [71, 72]. The features of various data formats for information modeling were summarized by [73]. Table 7 is an aggregated representation of [73]'s detailed study.

AutomationML is a kind of data format for the exchange of information based on XML, which is an open standard in IEC 62714 [74]. Goal of this standard is to realize the interaction among various heterogeneous manufacturing resources, because it can integrate several data formats into a unified format using a referencing framework. In this paper, AutomationML is suggested to be used for creating the CPPS instances owing to its vendor independency. AutomationML can store engineering information according to object-based charts, allowing physical and logical factory component models as data objects. Technically, the AutomationML engine can be employed to handle the related request that is based on AutomationML. As an integrating format, AutomationML is composed of the following standardized data formats: CAEX is used for modeling manufacturing systems (e.g., assembly line) topology information, COLLADA is used for modeling geometry and kinematic information, and PLCopenXML is used for modeling logic information, as shown in Fig. 8 [75].

Modeling CPPS by Automation ML can be achieved in three aspects: resource, process, and product, as shown in Fig. 9. This paper gives a case of Product, Process and Resource (PPR) for blisk manufacturing, as depicted in Fig.10. AutomationML is based on the following CAEX concepts [70], where these italic words refer to these defined elements in the schema of CAEX:

- *InstanceHierarchy* defines the topology of shop floor, such as production line, machining center, logistic unit, warehouse unit, and specific equipment.
- *RoleClass* defines a collection of possible functionalities that can be provided by the manufacturing resources.
- *SystemUnitClass* defines collections of vendor-specific solution equipment objects.
- *InterfaceClass* defines the interfaces that are required among SystemUnitClass and/or RoleClass.

**Table 6** Summary of standards relevant for enabling PPR data exchange [69]

| PPR category | Standards |
|---|---|
| Product date | DXF, DWG, CGM, HPGL, IGES, STEP, AP203, STEP, AP214, JT, VRML, X3D, STEP, AP239, AP242, and the OMG PLM services |
| Process date | OAGIS, ANSI/ISA-95, MTConnect, PSL |
| Resource date | CMSD, B2MML, STEP, AP239, and the OMG PLM services |

**Table 7** Requirement fulfillment of data formats

| Features | Date formats | | | | |
|---|---|---|---|---|---|
| | AMI | STEP | JT | XPDL | XML |
| Mechanical date | + | + | + | − | − |
| Electrical date | + | + | − | − | − |
| Process control date | + | − | − | + | − |
| Topological information | + | + | + | − | + |
| Establishing concept relationships | + | + | − | − | + |
| Tracing concept dependencies | + | + | − | − | + |

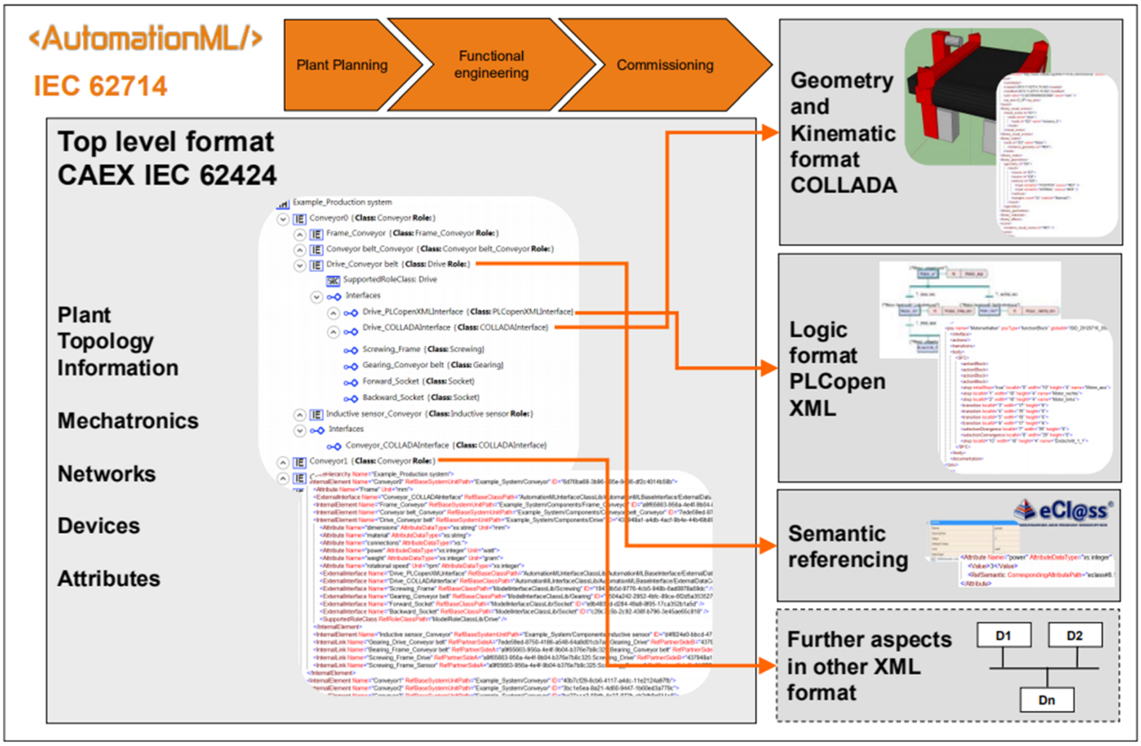



**Fig. 8** AutomationML base structure

In this paper, a specific CPPS is represented as an *InstanceHierarchy*. In *InstanceHierarchy*, each CPPS can contain many *InternalElements* with the same or different MCA models. For example, there is the same type of lathes that are owned by different MSPs. These lathes can be integrated and shared in the CPPS. MSPs can instantiate their own equipment according to the information models from the *SystemUnitClassLib*. The information models of manufacturing resources define the meta-data and contain the related properties, such as processing scope, machining accuracy, price, and period. These instances of resources can easily be removed, added, or updated in the CPPS, which is one of the important aspects of DT. MSC can select any instance that is most suited to the given manufacturing requirements of complex products.

An *InstanceHierarchy* can be composed of some elements (*InternalElement*). Each element corresponds to a physical manufacturing resource, which is modeled as "instances" that is *InternalElement* in the *InstanceHierarchy*. The type of each DT could be either *SystemUnitClass* or *RoleClass*, as each *InternalElement* is comprised of an instance of *SystemUnitClass* or *RoleClass*. The vendor-independent resources can be modeled by *RoleClass*, and vendor-specific resources can be modeled by *SystemUnitClass*. The interconnections between digital twins are represented as *InternalLinks*. All digital twins can be modeled as *SystemUnitClass* or *RoleClass* in the AutomationML format, while the relations among digital twins and the attribute of digital twins can be defined by the interfaces in

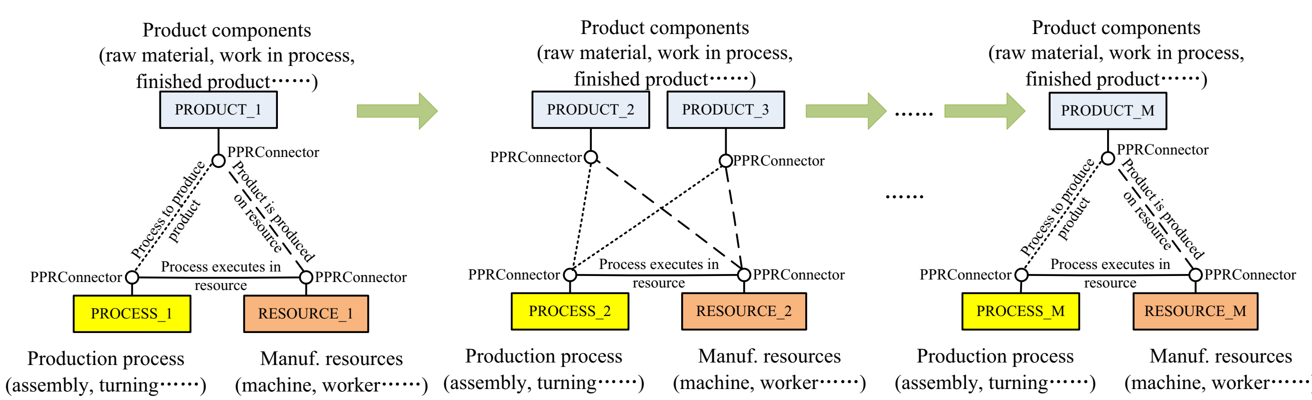



**Fig. 9** PPR model for CPPS

*InterfaceClass*, such as machining accuracy, location, and cost. The instance of *SystemUnitClass* or *RoleClass* corresponds to a specific value of these attribute elements.

The modeling steps of CPPS based on AutomationML are as follows (Fig. 11):

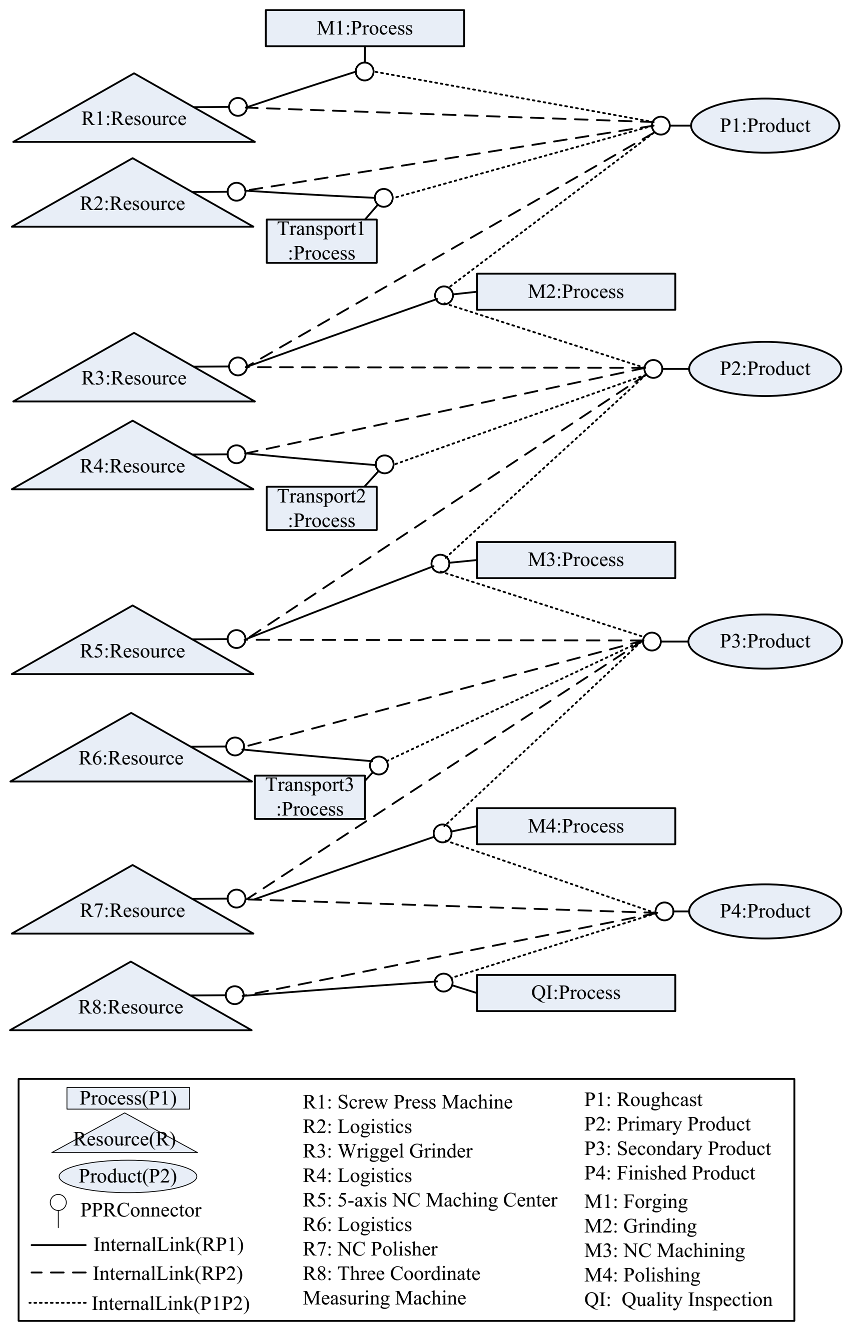
Step 1: The basic role class can be modeled by *RoleClass*. IEC 62424 has published the basic service classes for discrete manufacturing systems.

Step 2: The interface relation can be modeled by *InterfaceClass*, such as PPRConnector.

Step 3: MCA can be modeled as manufacturing services in the form of *SystemUnitClass*. These MCA models will be referenced and instantiated in *InstanceHierarchy*.

Step 4: Finally, a CPPS can be modeled by *InstanceHierarchy*, which contains the relevant *RoleClass* and *SystemUnitClass* that are MCAs. Thus the instance of *InstanceHierarchy* can represent the overall production process and reference specific production data in the shop floor. These models can be stored in the COLLADA format.

**Fig. 10** PPR case for CPPS



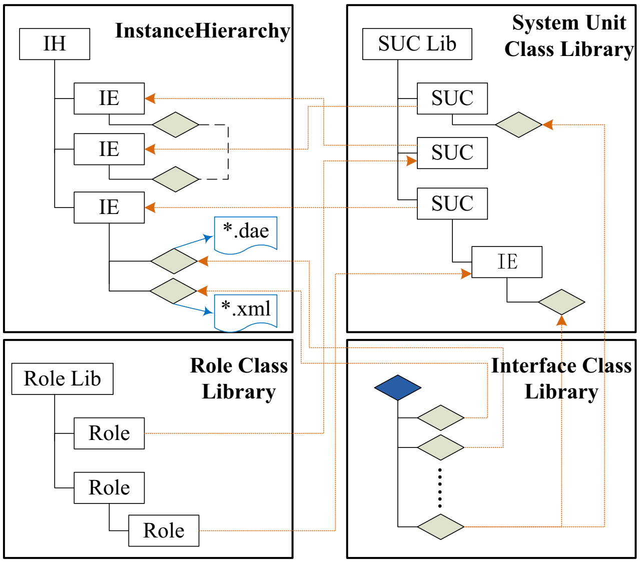



**Fig. 11** Modeling steps of CPPS

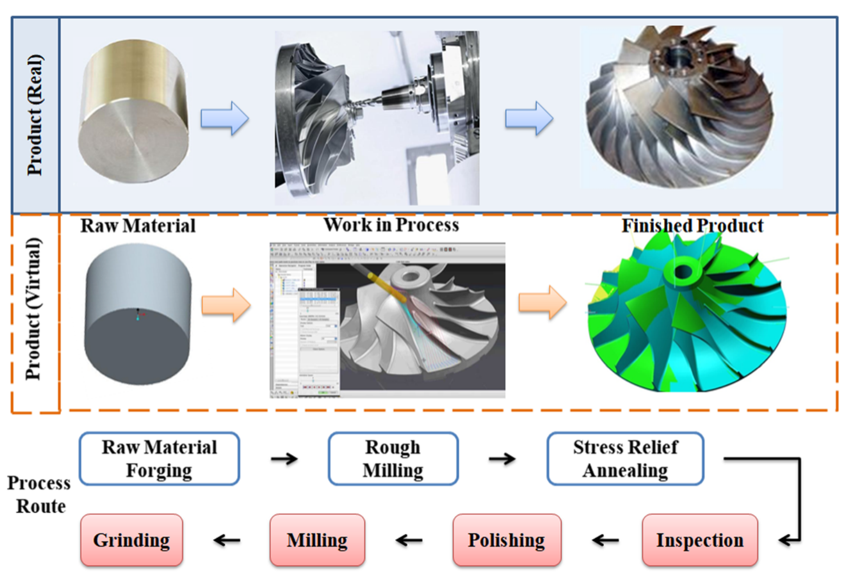
In AutomationML, the *SystemUnitClass* is a power way for modeling MCA. Any simple MCA may be used to compound and then complete more complex manufacturing tasks. In an engineering project, these MCA objects can be instantiated in an *InstanceHierarchy*. By using *SystemUnitClass*, each manufacturer can encapsulate own manufacturing resource as service. These manufacturing resources may be hardware (e.g., Forging Press, Polishing Machine, CNC Machining Center, 3D Coordinate Measure Machine, Logistics Vehicle) and may be software (e.g., CAD/CAM/CAE, PLM, ERP, CRM, MES). In CPPS model based on AutomationML, these manufacturing services are represented by instances of *InternalElement* in *InstanceHierarchy*. For example, there are six MSPs for the blisk production line. The first MSP has large tonnage screw press, which provides the manufacturing service of precision forging; the second MSP has high-speed peristaltic grinding machine, which provides the manufacturing service of precision forging; the third MSP has 5-axis CNC machining center, which provides the manufacturing service of turning, milling, and drilling; the fourth MSP has CNC polishing machine and 3D coordinate measuring machine, which provides the manufacturing service of the finishing polishing and quality testing of blisk; the fifth MSP has some logistics transfer equipment, which provides transferring service for blanks and parts among plants; the sixth MSP has screw press machine, which provides forging service.

### 4.3 Study of case scenario

In this section, a case of CPPS based on DT is presented to demonstrate how to model a blisk manufacturing shop floor. As shown in the top of Fig. 12, the physical blisk can be divided into three kinds that is the raw material, work in progress (WIP), and the finished product in the shop floor. In the virtual space, the virtual product is constructed corresponding to the physical blisk, as shown in the middle of Fig. 12. At the bottom of Fig. 12, the process route of blisk includes forging, rough milling, annealing, grinding, finished milling, polishing, and inspection. This above-proposed modeling approach can make it easy to create concrete instance of CPPS for blisk machining. The MCA can build its own digital twin through encapsulation and modeling.

In Fig. 12, the last four processes (in red) are the key bottleneck processes, which require expensive equipment and remain many technical challenges. This expensive equipment includes wriggle grinding machine, 5-axi NC machining center, NC polisher, and 3D coordinate measuring machine. Traditionally, the above five types of equipment for blisk manufacturing must be

**Fig. 12** Product and process route of blisk machining



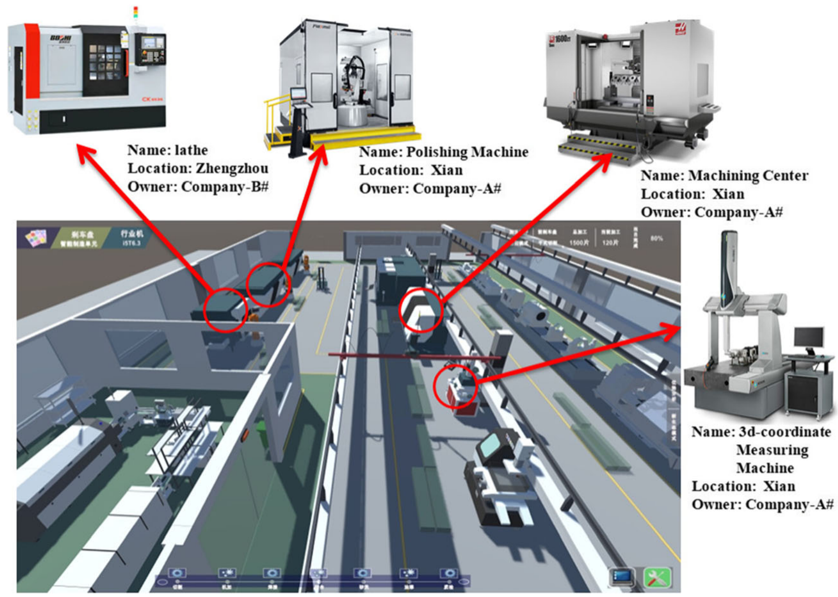



**Fig. 13** Experimental CPPS based on DT

located in a plant. However, based on CPPS, MSP with such equipment can participate in blisk processing and share their equipment. In-process products can be transported by logistics vehicles, even if the equipment is not in a plant. In CPPS, DT of this equipment will be integrated for monitoring the equipment and optimizing the manufacturing process.

Our research group has developed an experimental CPPS based on DT, which employs these development tools, such as 3D MAX (version 2018), Unity (version 2018.3.3f1), Sqlite (version 3.27.1), DB, Browser (version 3.11.0), and Visual Studio (version 2017). In order to develop digital twin of this plant, these 3D models of manufacturing resource are developed by 3D MAX, such as machine tools, robots, and forklifts. 3D models integration and GUI are realized by Unity 3D, such as the integration of plant 3D model, start and stop of equipment, production instruction. Sqlite, and DB. Browser is used as database for DT, which store some real-time production data, such as equipment status and production progress. As shown in Fig. 13, company A# has grinding machine, polishing machine, 5-axi NC machining center, and 3D coordinate measuring machine, which are located in Xi'an city, China. There need lathes for blisk manufacturing, but there is lack of this kind equipment in company A. These lathes owned by company B# can be integrated into CPPS via DT, although these lathes are located in Zhengzhou city, China.

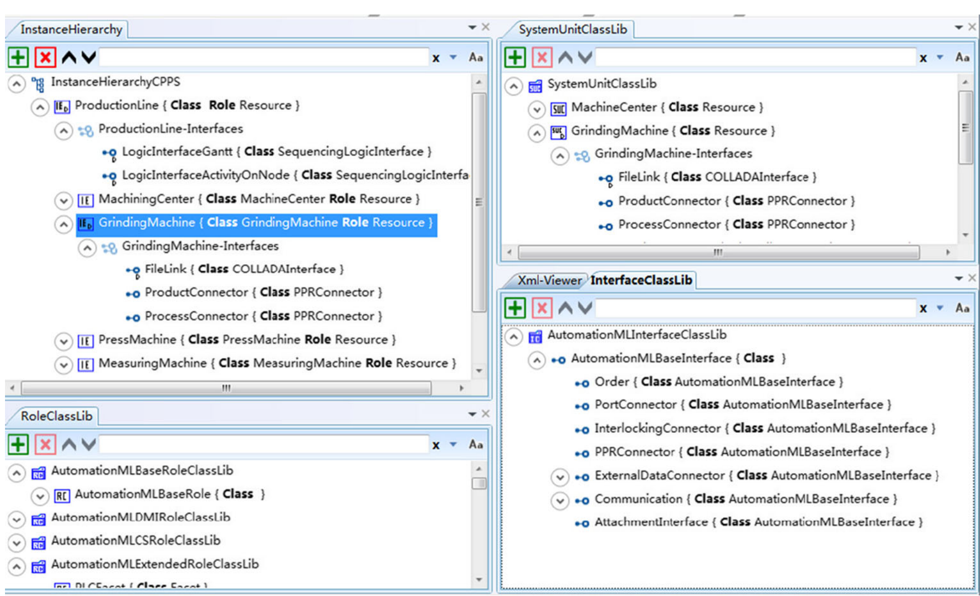



**Fig. 14** Modeling of CPPS

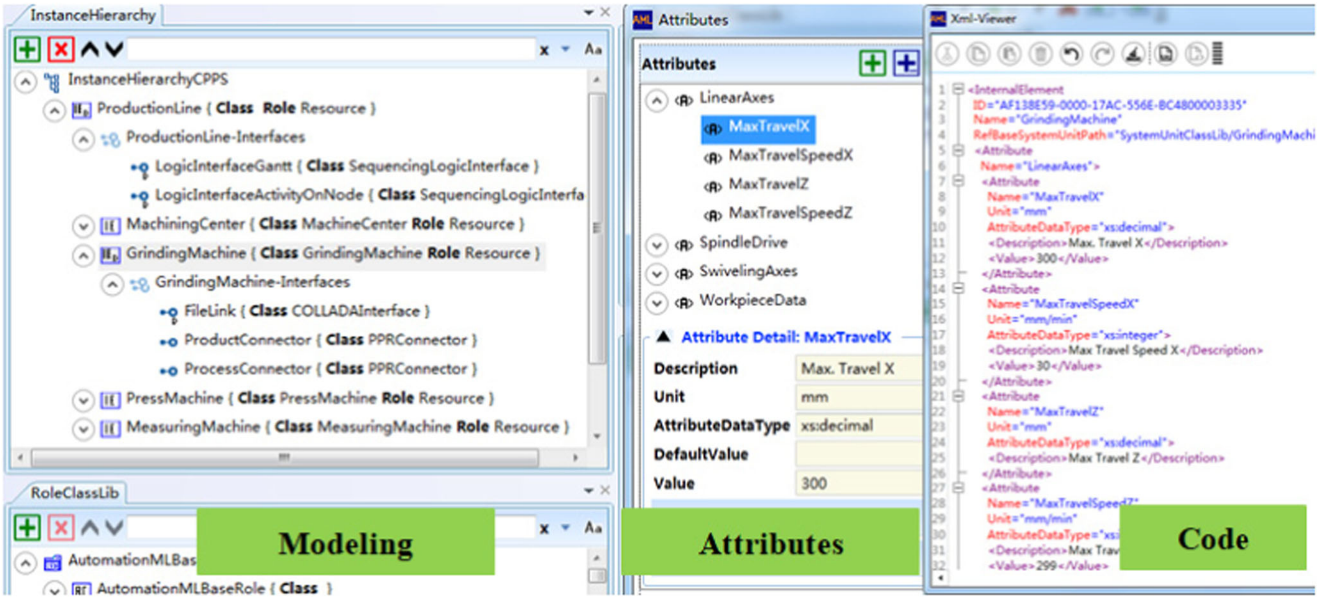
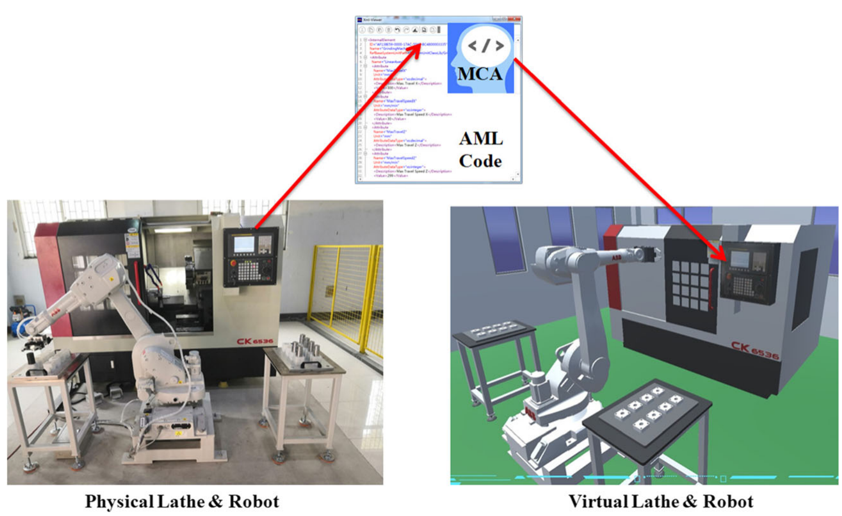



Fig. 15 Information modeling of MCA

According the modeling steps of CPPS based on AutomationML (section 4.2), there are four steps required to model the shop floor in this case. Firstly, define the basic role classes of manufacturing resources, such as lathe, milling machine, machining center, 3D coordinate measuring machine, and automated guided vehicle. Secondly, define the interface classes, such as PortConnector, PPRConnector, COLLADAInterface, and PLCopenXMLInterface. Thirdly, define SystemUnitClass for specific manufacturing resources according to the knowledge of industry field. Fourthly, create the *InternalElement* elements of specific manufacturing resource in *InstanceHierarchy*, and each *InternalElement* element must be referred to a specific *RoleClass* or a specific *SystemUnitClass*. Fifthly, the interface class is attached to these *InternalElement* elements to model the logical relationships with other elements; and finally, model these attributes of the *InternalElement* elements in *InstanceHierarchy* whenever applicable. All these manufacturing resources can be modeled by AutomaitonML, as shown in Figs. 14 and 15. The AutomaitonML code (middle of Fig. 16) for equipment (left of Fig. 16) is shown in Fig. 16. These codes will be updated to CPPS by MCA. The attributes of equipment can be gotten by parsing these AutomaitonML codes. These attributes can be shown in DT in CPPS, which is shown in Fig. 16 (right side). Through the experimental platform, it realizes the integration and sharing of resources, although all these resources are not located in the same plant and owned by one MSP.

Fig. 16 Digital twin of lathe and robot



## 5 Conclusions and future work

On one hand, more and more MSPs would like to share their own resources for more benefits of assets investment and the reduction of depreciation cost; on the other, MSCs would like to select some resources for a given project without large-scale asset investment. In order to achieve intelligent manufacturing, production systems are required to rapidly integrate these manufacturing resources and support information interaction between resources. CPPS has attracted more and more attention to reach the integration of manufacturing resources between the real space and the virtual one, so that the transparence and sharing of manufacturing resources can be realized. This paper introduces the concept and technology related to DT for CPPS, which converges with the advanced manufacturing and CPS in the context of industry. The formal and unified information modeling of CPPS are key factor to implement the CPPS in real production. Therefore, this paper firstly explores a generic architecture of CPPS based on DT. Then, an information modeling approach for CPPS based on AutomationML is proposed. Finally, this paper showed an experimental platform of CPPS via DT for blisk machining to validate the feasibility of the proposed modeling method. Through the experimental platform, the resources are modeled based on AutomationML and shared via DT. The next step is to research how CPPS can diagnose and predict their own state based on simulations. Then on base of diagnosis and prediction, we will focus on how CPPS reconfigures these parameters for production disturbances by robust scheduling.

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