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The Modeling and Using Strategy for the Digital Twin in Process Planning

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ABSTRACT Process planning is the core of guiding process production and one of the most critical parts to realize intelligent manufacturing of products. In order to realize the monitoring, simulation, prediction and control of the physical space in the intelligent manufacturing mode, the digital twin technology is used to guide the process planning. This research describes a modeling method of digital twin process model (DTPM) for manufacturing process and the contents of DT data, discusses the acquisition method of real-time data and the management method of simulation data. Aiming at the data fusion between physical space and virtual space, a hierarchical model and mapping strategy for multi-source heterogeneous data in machining process are proposed to generate the DT data. Finally, the guidance and the visualization function in process planning of DTPM is analyzed, and the effectiveness of this method is verified by choosing the design process of a key component in a marine diesel engine.

INDEX TERMS Digital twin, DTPM, process planning, data perception, simulation optimization.

I. INTRODUCTION

In recent years, with the advancement of Industry 4.0, computer-aided process design has ushered in a new stage. The new information technology such as big data, artificial intelligence and Internet of Things has developed rapidly. As a key trend of intelligent manufacturing, digital twin technology have widely applied in the process of production [1]. Under the demand of intelligent manufacturing, traditional process design has gradually evolved into intelligent, digital 3D process design. A new process planning model based on the multi-source data is born.

Realizing the information transmission, data sharing, real-time prediction, guidance feedback and high integration of manufacturing between physical space and virtual simulation space is gradually becoming the basis of intelligent manufacturing. As the most promising means to support the virtual and real integration, digital twin technology is gradually becoming the key technology to guide the processing industry from traditional mode to intelligent manufacturing [3].

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Process specification is a technical document for the manufacturing process and operation method of the product [4]. It is not only a disciplinary document that all production personnel should enforce strictly and implement conscientiously, but also the basis for product preparation, production scheduling, worker operation and quality inspection. Process model is an important basis for guiding actual processing, a link between design process and actual processing. Process model provides a key basis for reflecting the overall manufacturing level, productivity level and production quality index of enterprises [5]. The traditional one-way manufacturing information transfer method of "design → process → manufacture → inspection" is gradually replaced by multi-directional integration method based on the Model-Based Definition (MBD) technology. Now, MBD technology has been further developed and applied in product design, process design, casting design, etc. [6]. Simplifying process planning by reflecting product design information, geometric information and process information with highly integrated 3D model, is becoming the mainstream way of modern process design and production [7]. At present, MBD process model which can guide actual production only provide static process template. In view of the real-time dynamic processing problems in complex manufacturing environment, the existing process models cannot provide the enterprise with corresponding solutions. The information provided by process models has great simplicity, limitation and closeness. A technique for real-time monitoring and dynamic feedback of various states and parameters in machining process and a process model that can express data in the process of digital manufacturing of products are urgently needed to be developed. As the key technology of cyber physics system developing, digital twin technology can effectively integrate and manage multi-source heterogeneous data in product life cycle [8]. Theoretical research and wide application of digital twin have made it possible to deepen and develop MBD technology.

The paper is organized as follows. The DTPM and DT data are defined in detail in Section 3. In Section 4, the overall technical route is expounded; then the DT data framework of DTPM and the hierarchical data model is constructed. The methods of acquiring heterogeneous process data are put forward and the virtual-and-real data mapping platform is established. Thus, generating DT data for machining process. In Section 5 the DTPM is created and the operation process of the DTPM is determined; Finally, the validity of this method is verified based on the key components of marine diesel engine in Section 6. Section 7 concludes the practical significance and innovation of the proposed method.

II. RELATED WORK

A. 3D PROCESS PLANNING

1) MBD PROCESS MODELS

With the development of information technology, Computer Aided Process Planning (CAPP) has replaced the traditional handicraft technology and became the main way of current process planning [11]. Traditional process model is a simple design model. It has gradually evolved into a multi-domain digital process model that can express process design intentions, process information and even product life cycle data. The process model has evolved from a 3D solid model containing only size information to a 3D process model based on MBD. It can basically realize the rapid design of 3D model parts, the acquisition, expression, traceability, storage and correlation technology of process information. The established 3D process model can express the processing state of parts through the inter-process model. It visualizes the processing of parts. The earliest CAPP systems were developed based on two-dimensional engineering drawings. Geometric model and process information are separated from each other. But nowadays, 3D MBD process model is developing rapidly. It provides new technical support for industrial manufacturing [12]–[15]. Qiao *et al.* [16] proposed a 3D process model with geometric evolution and multi-perspective of process information, which can comprehensively describe and express process information. This study promoted the generation and optimization of digital process information. The existing process model based on MBD technology has been applied in the field of aircraft manufacturing, ship manufacturing. Lin *et al.* [17] proposed a 3D process planning method based on MBD processing unit for solving the problem of inconsistent information in 3D process planning; Alemanni *et al.* [18] focused the attention on a method for supporting the MBD implementation and proposed the data structures; Huang *et al.* [19] proposed a MBD model with multi-level structured manufacturing reusing based on processing features, which can capture abstract information, detailed feature interaction information and processing semantic information involved.

2) MANAGEMENT AND REUSE OF PROCESS INFORMATION

Reasonable expression and management of process information is the key to improve the efficiency of 3D process planning. Expressing process information clearly, store and manage massive process information, and Ensuring the timeliness and real-time sharing and reuse of process information transmission have become important factors restricting the low efficiency of process design. Beranrd and Perry [20] defined the product process model based on knowledge association, which is helpful to process decision-making and process reuse. Zhang *et al.* [21] integrates public welfare resources and related information by using the processing semantics of two-dimensional engineering drawings and the processing process model. Fu-Jun *et al.* [22] put forward the method of creating process model by process knowledge, and the method of creating process model by positive and reverse sequence. Substantial research effort has pursued the similarity-based retrieval methods to support process knowledge reuse, and it mainly included text-based, content-based, shape-based, topology-based, and feature-based retrieval methods. Zhang *et al.* [23] proposed a comprehension reuse method with different manufacturing resources; according to the emerging collaborative technologies, Peng *et al.* [24] designed and developed a smart collaborative system to streamline the design process as well as to facilitate knowledge capture. Content-based retrieval mainly includes shape-based and annotation-based retrieval methods. Lee *et al.* [25] described a model for knowledge management and collaboration in engineering change processes and built a prototype system by using the case-based reasoning method.

With the rapid development of MBD technology and information management technology, the realization of high integration, sharing and efficiency of information has become the focus of process planning. It is an urgent problem to push on and deepen MBD technology by using new information technology to realize more effective 3D process planning.

B. APPLICATION OF DIGITAL TWIN

1) APPLICATION AREA BASED ON DIGITAL TWIN

As a key enabling technology to solve the problem of Information Physics integration in intelligent manufacturing and to implement the concept of intelligent manufacturing, digital twin technology is becoming more and more mature [26]. It has been introduced into more and more fields by industry for landing application. Digital twin technology originated from the demand of aerospace field, and now it is gradually expanding to the civil field. Tao and Zhang [27] discussed the application of digital twin technology in depth, and put forward the main problems to be solved and ten application fields of digital twin technology in the future; Zhang *et al.*[28] used digital twin technology to optimize the production line of hollow glass. He proposed three key technologies to enhance the performance of digital and analog production lines in the real world; Qi *et al.* [29] elaborated on the concept of digital twin, as well as the changes it brought to intelligent manufacturing and its application. Tuegel *et al.* [30] put forward the technology of aircraft structure life prediction based on digital twin Technology. This indicates that digital twin technology will be a practical application technology oriented to product life cycle. The landing of digital twin technology requires certain technical support. Its primary task is to establish the digital twin model of application objects, and then to promote the application of related fields by building multi-dimensional, multi-scale and highly integrated digital twin model.

2) PRODUCT LIFE CYCLE MANAGEMENT BASED ON DIGITAL TWIN

Product Lifecycle Management (PLM) is the most effective way to manage the business activities of a company's products throughout its life cycle [31]. From the first concept of product to scrap and recycle, the whole life cycle of product should include design, test, manufacture, assembly, operation and maintenance, scrap and recycle. At each stage, a large amount of heterogeneous multi-source data will be generated. Corresponding management and decision-making for different stages of data has become an important indicator reflecting the core management mode of enterprises and the level of product intelligent manufacturing. Establishing digital twins in different stages of product life cycle, establishing multi-scale and multi-physical field coupling model, processing large-scale databases, quantifying uncertain parameters, implementing sensor measurement and improving performance calculation capability are key technical problems to be solved urgently [32]. Aircraft digital twins for Aeronautics can dynamically adjust their models by receiving data from different stages of the whole life cycle of the engine [33]. It keeps a high degree of consistency with the actual engine in real time. It can also predict and monitor the operation and life of the engine. Tao*et al.* [34] proposed a new method of product design, product manufacturing and product service driven by digital twin, aiming at solving the problem that the current research only focuses on the physical world and neglects the virtual world. He developed a specific application method and framework for digital twin-driven product design, manufacturing and service. This provides a new idea for product life cycle management and big data processing. Digital twin technology shows the potential and important role of real-time data acquisition in production system, Thomas [35] introduced the potential and advantages of real-time data acquisition and subsequent simulation data processing based on learning factory.

3) PROCESS DESIGN BASED ON DIGITAL TWIN

The sustained advancement of Industry 4.0 requires the support of new front-end technologies. As the core of product development, process design plays an important role [36]. Its execution will directly affect the downstream manufacturing level. Therefore, the research on process planning must break through the existing 3D MBD model. Research needs to integrate physical spatial data with virtual spatial data. The model should give more precise guidance to the actual process design. The new generation of computer aided process planning, which integrates digital twin technology, is one of the core development directions of product digitalization. Yu and Hu [37] introduced the concept of implementation model to solve two problems in current CAPP research. She proposed the design framework of CAPP in digital twin environment. Product model can effectively evaluate the impact of process decisions on the quality and function of mechanical products. However, the current digital twin method lacks conceptual basis. This hinders the development of the applicability of digital twin technology in various activities of design and production engineering. To address this problem, Schleich *et al.* [38] discussed model conceptualization, model representation and model construction. He also pointed out the application of digital twin technology in product life cycle. This lays a theoretical foundation for the application of digital twin technology in process design; The network physical production system based on digital twin is a key boost to industrial 4.0. Uhlemann *et al.* [39] studied the acquisition and management of automated data. He put forward practical methods for real-time evaluation and analysis of highly complex production systems depending on real-time database. Miller *et al.* [40] pointed out that on the basis of the 3D MBD model, the basic concept of digital twin should be integrated, the potential value of the CAD model should be expanded, and the visualization of data should be expanded.

The modeling theory derived from digital twin is gradually increasing, and the practical application examples driven by digital Twin are also growing [41]–[43]. Collaborative manufacturing and intelligent manufacturing driven by digital twin have become the current research direction and manufacturing innovation trend.

III. BASIC DEFINITIONS AND OVERVIEW OF METHODOLOGY

A. BASIC DEFINITIONS

Digital twin model is an integrated, multi-physical, multi-scale and probabilistic high-fidelity simulation model for the system under construction. Digital twin technology relies on

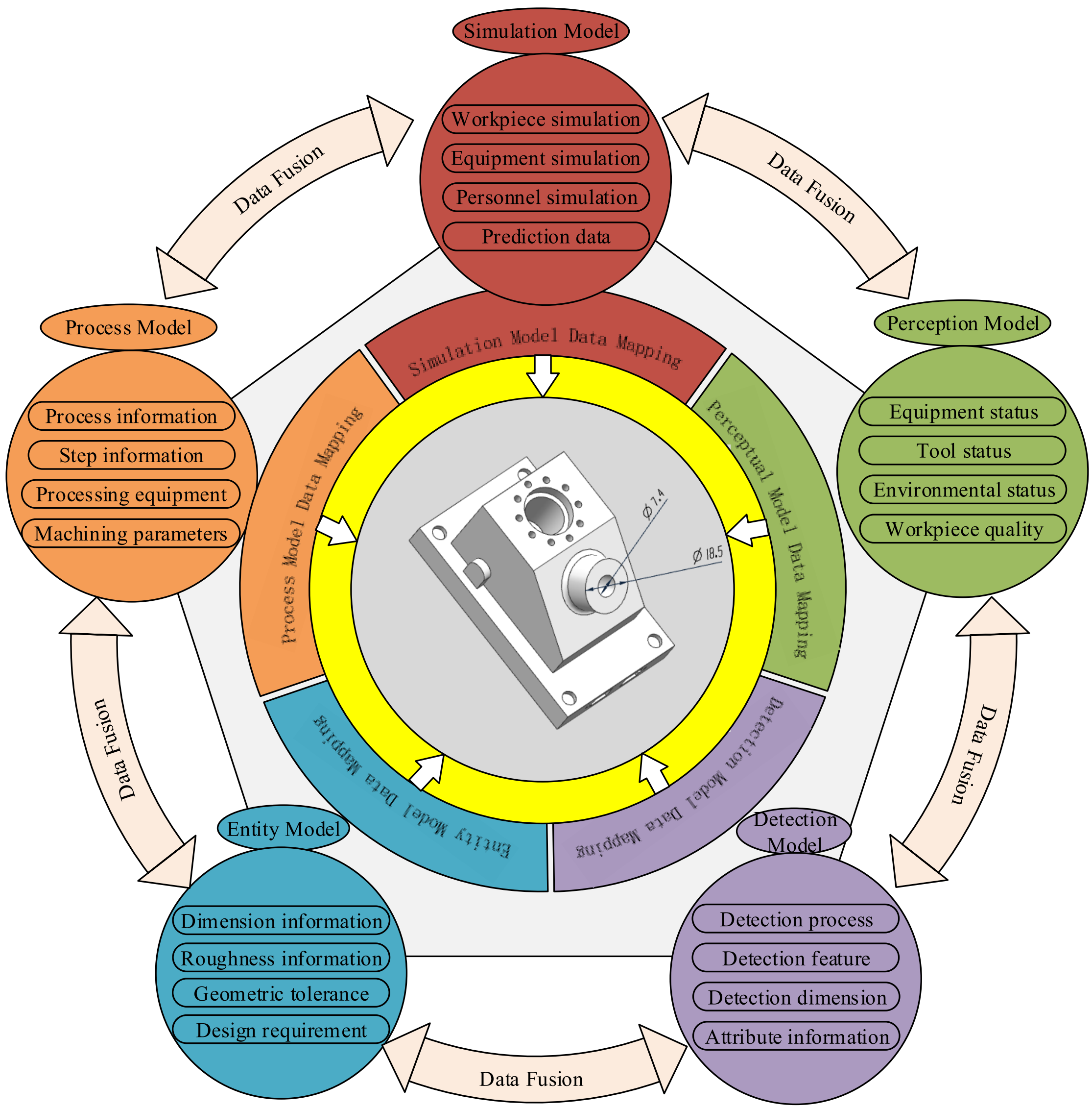


FIGURE 1. Definition of DTPM.

high-precision model, sensor information, historical data and input data. It uses this information to complete the mapping and prediction of the operation and performance of real physical twin entities throughout their life cycle. Therefore, the construction of digital twin model is the basis of realizing digital twin technology. MBD process model is a complex 3D model including product geometry information and processing information. Digital twin model is its deepening model. The process model based on digital twin should be a high-fidelity model that integrates the information and more product life cycle data as shown in FIGURE 1. In this paper, the DT data oriented to machining process and the DTPM are defined.

Definition 1: Digital Twin Process Model (DTPM) DTPM is a high fidelity model that can reflect the real-time state and simulation results of physical space in machining. It is a complex model that covers all information of model layer (M), data layer (D) and relationship layer between model and data(R).

$$\mathrm{DTPM} ::= \mathrm{M} \cup \mathrm{D} \cup \mathrm{R} \tag{1}$$

$$\mathrm{DTP}M_i = \{BM, WPM_i, PPM_i, PSM_i\} \tag{2}$$

$$\mathrm{WPM}_i = \{\mathrm{MFV}_i, \mathrm{APM}_i, \mathrm{BM}\} = \{\mathrm{FDM}, \textstyle\sum_i^n \mathrm{MFV}_i. \tag{3}$$

The model layer includes Blank Model (BM), Working Procedure Model (WPM), Process Perception Model (PPM)and Process Simulation Model (PSM). WPM is made of Manufacturing Feature Volume (MFV)of traditional MBD model, BM and After Processing Model (APM). i in the formula represents the procedure i. These models include corresponding data of dimension information, design information, process information, perception, simulation, operation history and prediction. DTPM is formed by data mapping and model integration. Finally, DTPM with high integration and fidelity is used to express the whole life cycle data of process-oriented products.

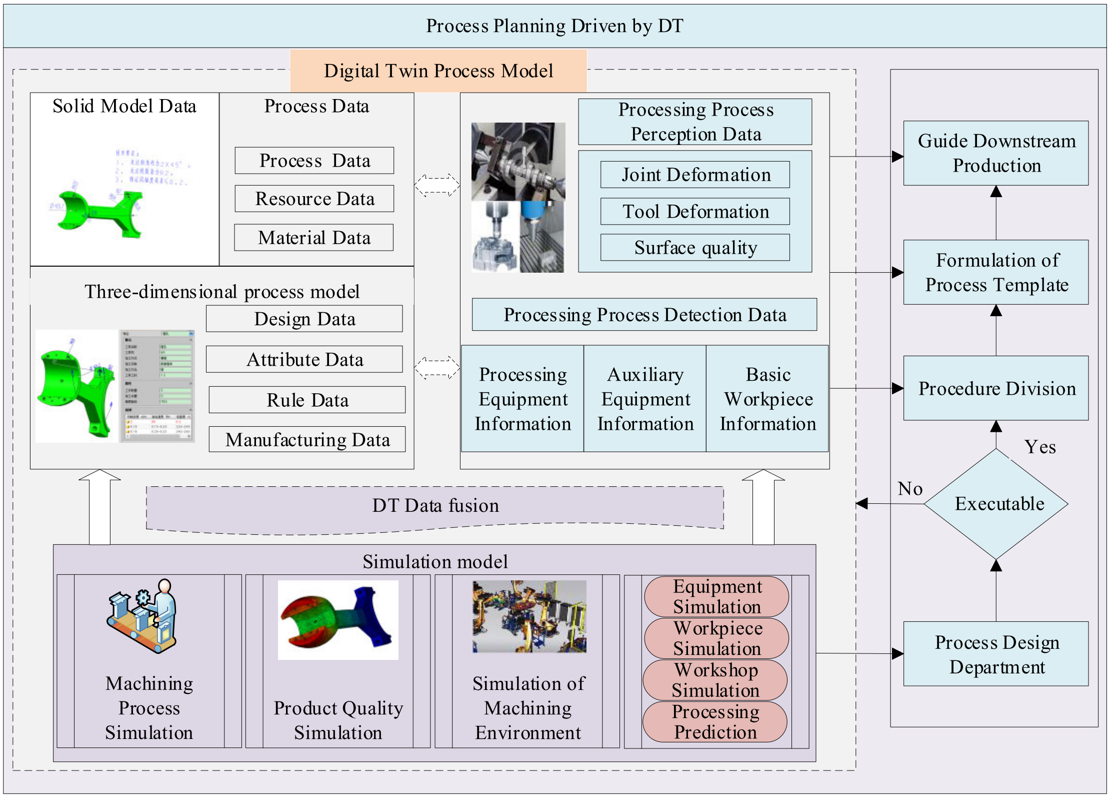


FIGURE 2. **Design flow of DTPM in process design.**

Definition 2: Digital Twin Data Based on Process Model (DTD-PM) The process model is the most important basis for guiding downstream production. It should cover massive multi-source heterogeneous data for product processing. Compared with complex model of multi-reference model in traditional process design, DTPM provides a highly integrated model which includes BM, WPM, PPM and PSM. It provides effective supporting data, convenient model and high precision simulation results for product life cycle design and prediction.

$$DTD - PM = \{DD, PPD, PD,HRD, SD\} \tag{4}$$

$$PDD = \{PEPD, JRMD, EPD\} \tag{5}$$

$$PD = \{PAD, PRD, MD\} \tag{6}$$

DTPM is a highly integrated model that integrates multiple models, and the DT data will be huge. Therefore, the model should be composed of Design Data (DD), Process Perception Data (PPD), Process Data (PD), Historical Running Data (HRD) and Simulation Data (SD) for the whole life cycle of product processing. What's more, PPD involves three aspects: machine, material and environment. It is constituted by Processing Equipment Perception Data (PEPD) and Environment Perception Data (EPD). Process data consists of Process Attribute Data (PAD), Process Rule Data (PRD) and Manufacturing Data (MD).

In order to rapidly establish the DTPM which can guide the whole life cycle of product processing process, the design data, process data, process perception data and simulation data need to be elaborated in this paper. Design data should include not only dimension information, geometric tolerance and accuracy requirements, but also the relationship between design data (feature topology). Process data should include not only process attribute information, process rules information, process resources and equipment information, process card information, but also processing parameters and processing capacity of processing equipment under process rules. Processing perception information includes not only the state information and time information of human beings, but also the real-time detection information of workpieces, equipment and personnel. The simulation data should be composed of real-time simulation data, prediction data and optimization data. The sources of these data include processing equipment, workers, workpieces and even the whole workshop.

B. OVERVIEW OF METHODS

On the basis of traditional process design, process model realizes the integration of 3D design model and process information. Using a single process model to reflect the geometric information and process information of parts processing improves the executability of the process. However, the field data processing and guidance role of real-time virtual simulation has not been deeply studied. In this paper, the creation method of the DTPM is proposed and shown in FIGURE 2.

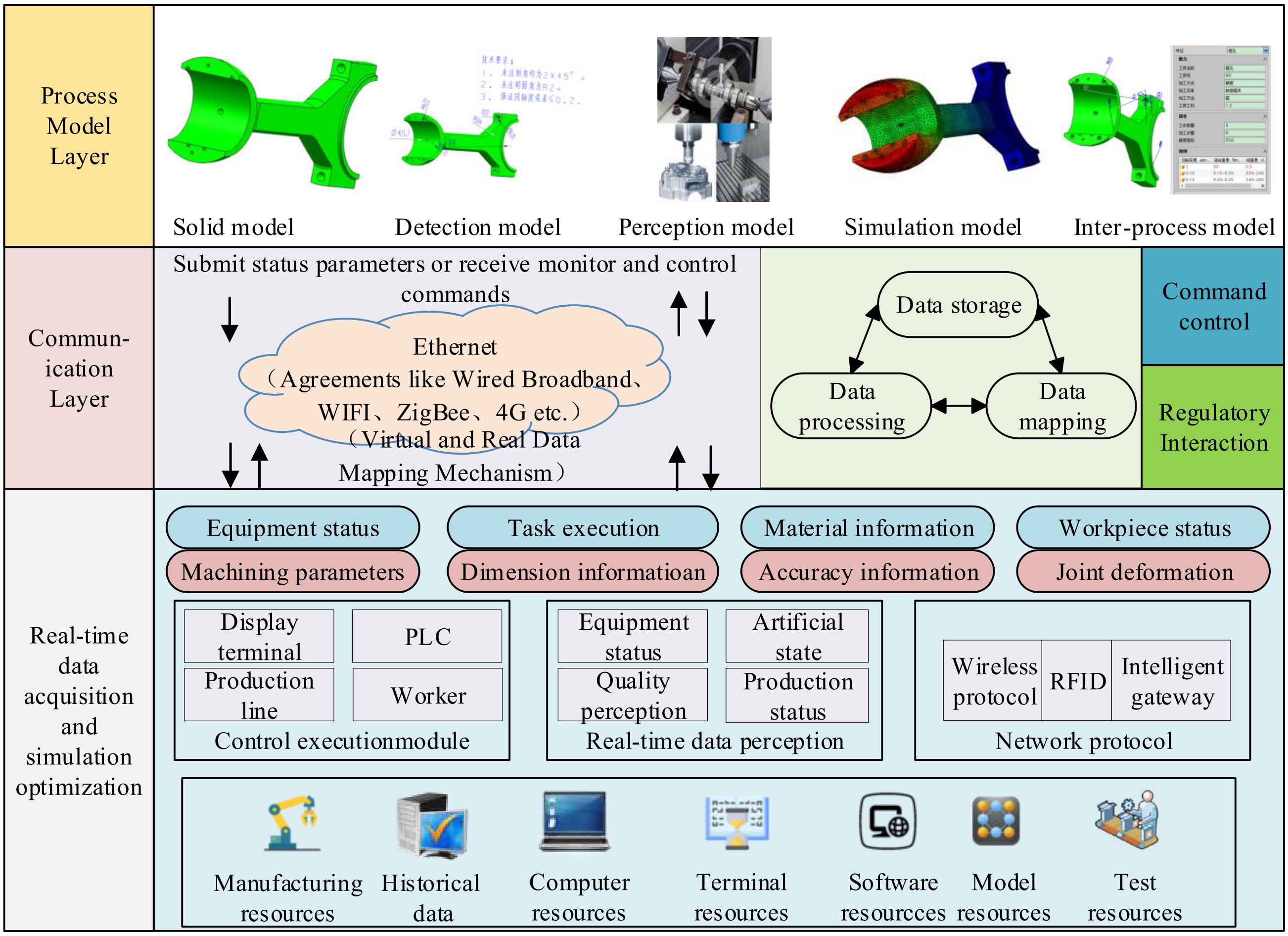


FIGURE 3. The modeling framework of DTPM.

3D solid model, inter-process model, process perception model and simulation model are constructed based on multi-physical, multi-disciplinary and multi-scale massive data. The DTPM is fused by integrating and mapping massive data. DTPM is the core of the whole process design process. Processing perception data and virtual simulation data are innovation points of DTPM. It is the basis of driving model different from MBD model. The acquisition of perception data is achieved by deploying Radio Frequency Identification (RFID) and sensor-led multi-agent devices.

From the overall process of DTPM, it can be seen that process model is the core of process design. DT data is the basis of process model. Perception data and simulation data are the key to embody the digital twin technology. The ultimate goal is to formulate the process template and guide the processing and manufacturing.

IV. ACQUISITION AND MANAGEMENT OF PROCESS DATA

A. FRAMEWORK OF DT DATA

In order to achieve high fidelity of digital twin model, the modeling framework of DTPM is constructed as shown in FIGURE 3. The framework consists of data acquisition layer, simulation and optimization layer, communication layer and creation module of process model. Data acquisition layer is based on adaptive sensing equipment. The simulation optimization layer is based on virtual simulation software. Communication layer is based on network protocol. The creation module of process model is driven by DT data. The processing data can provide real-time, effective, reliable and meaningful data source for virtual space simulation and optimization. As a bridge connecting the physical world and virtual space, the communication layer maps data from physical space to virtual space for prediction. It feeds back the virtual space data to the physical space to guide the actual processing and production, and accurately maps the physical data and virtual data in the human-machine-object-environment. So, it is the basis of DT data of process model. The simulation data of virtual space and the results of prediction are the core of guiding physical production, the embodiment of digital twin technology, the deepening of DTPM in traditional machining technology, and one of the data sources of process model. The final process model is composed of 3D solid model, process model, perception model and simulation model. The highly coupled integrated model is an important basis for guiding downstream production and processing.

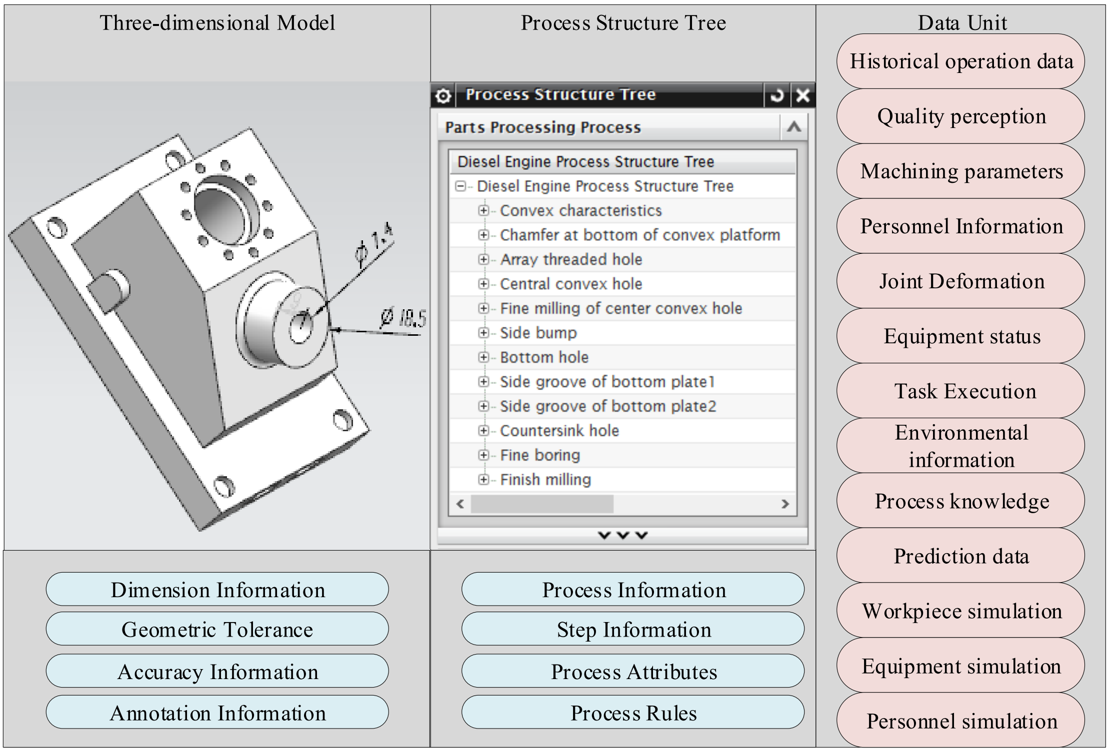


FIGURE 4. DT data for process design.

The DT data should cover both static data and dynamic data (data of process design and data of process perception). These data are mainly composed of manufacturing resource data, computer resource data, historical data, simulation data, real-time data collected during processing process, part attribute data, process attribute data, process labeling information and so on. The process data collected is combined with traditional process design data, historical data and simulation data to build the DTPM. Perception data and simulation data become the most important two parts of the DTPM, which are the key differences from the traditional process model. These two parts of data are displayed in the DTPM through the corresponding integration and mapping relationship, and the DT data achieves a high-fidelity state of multi-dimensional and multi-physical quantities in the processing process. The processing information of parts should not only include the attribute information of parts (material, model version, etc.), information of process attribute (processing method, equipment resources, etc.), information of process feature (feature attribute information), information of process labeling (size, roughness). They can only represent the process information before or after the parts are processed. It should also include the information of real-time equipment, information of personnel and information of workpiece during the actual processing.

After the interaction and fusion of all elements, processes and business-related data (such as perceptual data, process design data, virtual simulation data), the DT data for process design is created as shown in FIGURE 4. Perception data includes the data collected by RFID technology, tool status data, deformation data, logistics information, real-time power of servo motor and real-time speed of motor shaft. These data intuitively reflect the real-time status and quality of the part in processing. The status of manufacturing resources in processing are also be reflected. The virtual simulation data is obtained by the results from software simulation and algorithm optimization. The simulation data contains the data of workpiece, equipment, personnel and environment. The optimization data includes the data of the processing method and the algorithm of the processing flow. Virtual data continues to compare with history operational data and provide the history operational data with an update. Then a predictive data basic and guidance scheme for on-site processing can be provided.

B. DESCRIPTION AND ACQUISITION OF REAL-TIME DATA OF MACHINING PRODUCTS

In the mode of intelligent manufacturing, processing equipment and workpiece are the core units of manufacturing. Real-time data appearing in the actual processing of workpiece is the data that can reflect the real situation of workpiece, processing equipment and processing environment. It is also an important basis for evaluating the performance of the whole processing. If these data can be integrated and utilized, it will be of great significance to guide the actual production.

Real-time data of processing process are those that cannot be obtained directly and update with the change of the

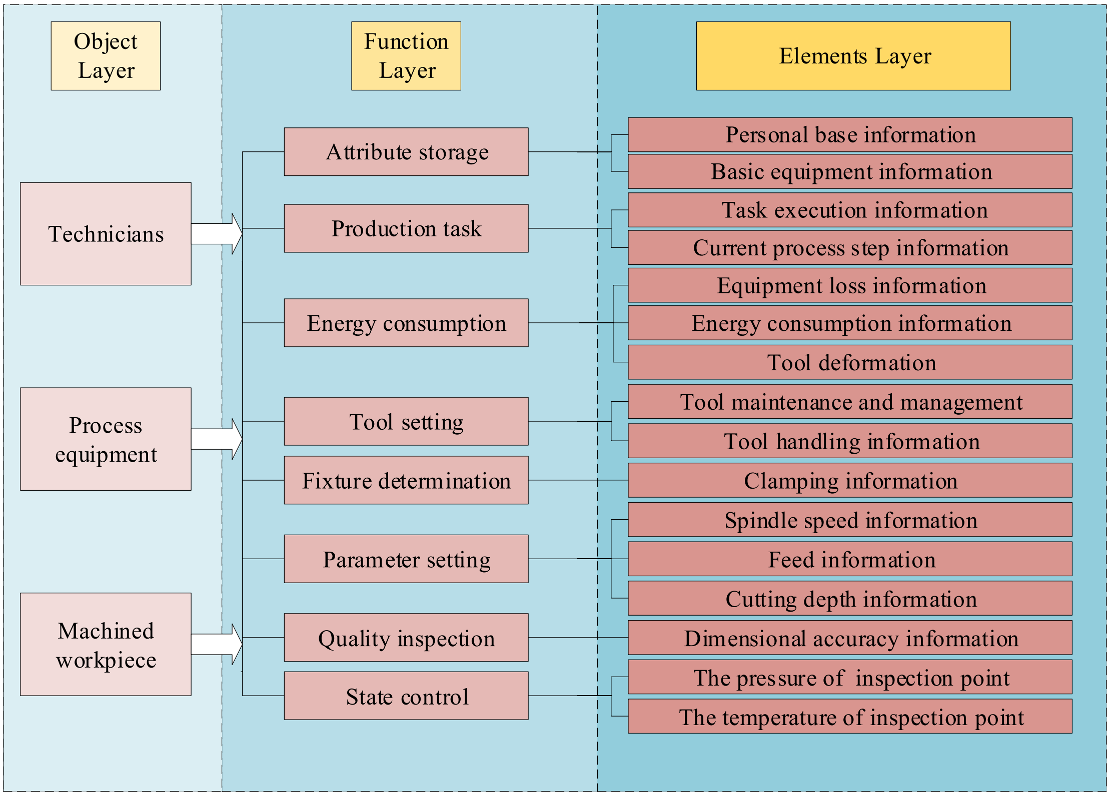


FIGURE 5. Hierarchical model of real-time data in machining process.

state of the product. Dynamic data are acquired through auxiliary equipment. Real-time data is composed of a large number of heterogeneous and complex data, as shown in FIGURE 5. Dynamic perception data directly reflects the real-time information in the process of processing, which determines the quality and success of the actual processing. The quality of finished products is the fundamental purpose of enterprise workshop manufacturing. Therefore, dynamic sensing data is the key to guide the upper process design, actual manufacturing, scheduling of processing tasks, equipment maintenance and quality control in manufacturing. The collection, management and application of multi-source heterogeneous information must be realized in the whole process planning.

The acquisition method of process data mainly includes two ways as shown in FIGURE 6. One method is using the secondary development of software through interface protocol. To collect data, the other is adding sensors in machine tools to realize the acquisition. Software acquisition mainly includes: CNC system of CNC equipment, PLC system, machine tool electronic control system and the analysis management system of production data and equipment status information. The analysis management system is mainly used to collect and analyze the working and running state data of production equipment, to monitor the real-time production status of equipment and workpiece, and to provide support for other software systems.

C. DESCRIPTION AND ACQUISITION OF SIMULATION OPTIMIZATION DATA

The process model has the function of guiding and predicting the actual process design and downstream manufacturing. In this paper, based on the perceptual data of processing process, the object of virtual simulation is determined. The optimal or better simulation results can be obtained by using the simulation of actual object and the algorithm optimization of the process flow as shown in FIGURE 7. The simulation data are integrated into the process model to promote the multi-dimensional and multi-scale deepening of the process model.

Virtual simulation mainly relies on software, algorithm and process object to get the preset results. Firstly, virtual simulation is the simulation of the production process of processing equipment, personnel and parts in the workshop. While confirming that the overall production operation can be realized, the production cycle can be shortened and the better resource utilization can be achieved. Secondly, multi-disciplinary simulation of material mechanics, thermodynamics and dynamics of workpiece is carried out. It is necessary to inspect whether the processed parts are qualified or not in order to reduce the processing error caused by the blank before processing. Secondly, the processing capability of the equipment is simulated to verify whether the processing equipment has the processing conditions to complete the upcoming process, so as to reduce the processing error and the

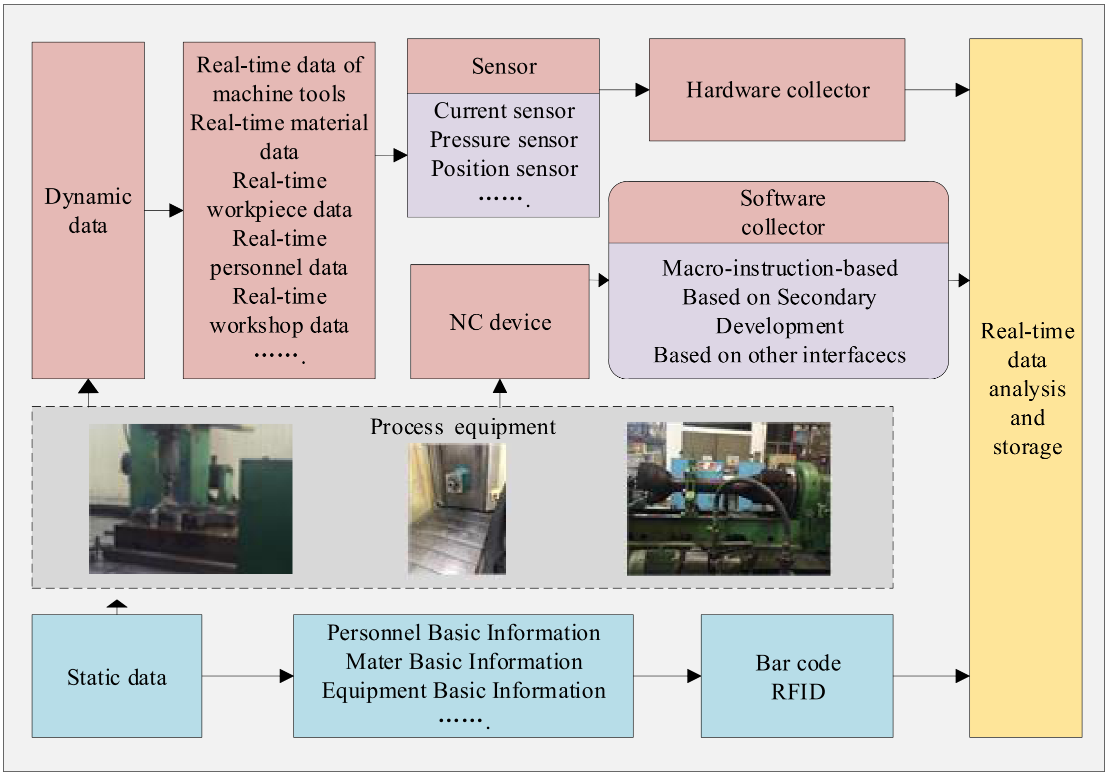


FIGURE 6. Acquisition of real-time field data.

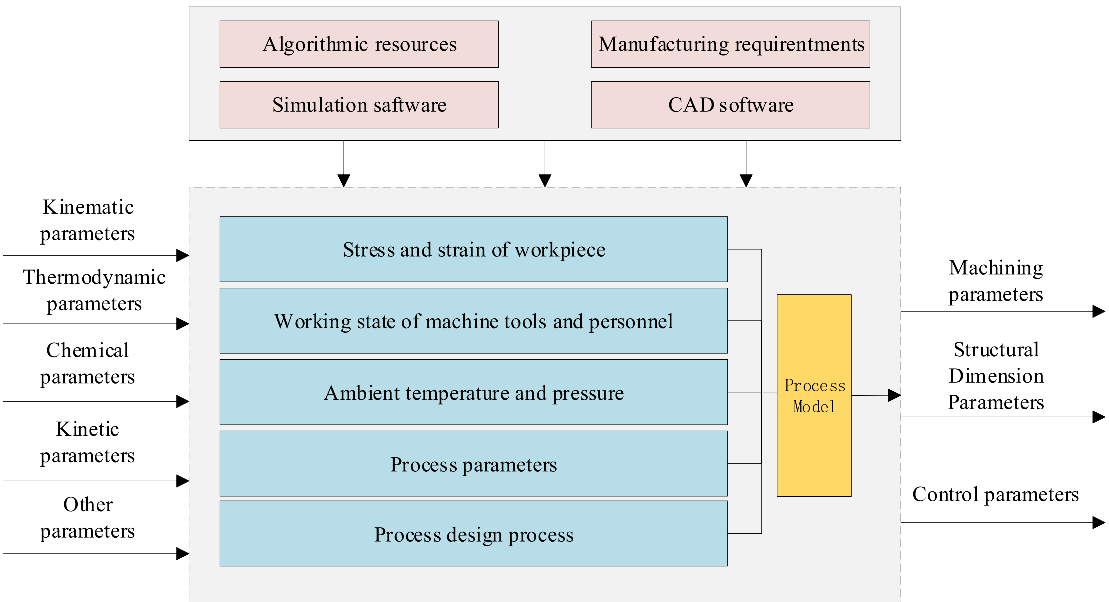


FIGURE 7. Integration of simulation data and optimization data.

occurrence of equipment failure. Finally, the workpiece after processing is simulated according to different requirement. For example, whether the workpiece satisfies the conditions for entering the next process and whether it meets the production requirements after the inspection process is completed. Virtual optimization refers to the algorithm optimization of production resource scheduling, processing route, workpiece design parameters, and workpiece quality caused by different processing parameters of equipment. In this way, the real-time and efficient utilization of workshop personnel, equipment and workpieces, the reasonable arrangement of processing route, the reasonable determination of workpiece design parameters and the correct selection of processing parameters can be realized. By using virtual simulation of software and intelligent iterative optimization of various algorithms, the DT database of process model is greatly expanded, and the multi-dimensional and multi-disciplinary nature of DT data is promoted. Massive multi-source heterogeneous data will achieve high fidelity and accurate prediction of process model. Massive multi-source heterogeneous data ensure high fidelity and prediction accuracy of process model.

D. GENERATION AND MANAGEMENT OF DT DATA

There are some problems in traditional process model theory, such as weak correlation between process model and design model, between geometric information and non-geometric information, between process model and process resources and equipment. Most of the data are relatively independent and scattered, computer recognition is difficult, and there are data islands. For DTPM, the data island is magnified when new field sensing data and simulation data are added. At the same time, data integration and sharing are essential. Data mapping, integration and sharing are realized by redefining process information, expressing process design intention and determining process information data carrier. Data can be centralized and managed effectively.

This paper presents a data mapping technique based on the established DTPM. Multi-source heterogeneous information, multiple physical interfaces, heterogeneous driver protocols and data parsing are included. Sensor data acquisition is realized through physical interface and data sharing in the system is realized by driving protocol. With the help of multi-dimensional perceptual information analysis technology, a standard data description format is established. Data carrier, data attribute, data source and other information are mainly expressed. Secondly, the relationship between multidimensional perceptual data is analyzed. The relationship between the available information resources data and the data needed for the final DTPM modeling is analyzed, such as the real-time perception of the relationship between the processing time of equipment and the time-consuming process, the relationship between the processing parameters of machine tools and the surface quality of final products, etc. Using massive multi-source heterogeneous data, the cooperative coupling relationship of DT data is analyzed, and the technical route of DT data interactive mapping is constructed as shown in the FIGURE 8. A unified data architecture is constructed and database software is used to format data to achieve a unified format, lightweight data, convenient data storage, management and application.

V. CONSTRUCTION OF DTPM

A. FRAMEWORK OF DTPM

DTPM is a deepening of process model definition based on MBD model, and a derivation of digital twin technology for process planning. Essentially, based on the existing design data and process data, a digital virtual model is constructed by integrating historical operation data, process perception data and process simulation data, which can reflect all the data needed by the actual processing parts in real time. Finally, feedback to upstream process design and guidance to downstream processing and manufacturing are realized. FIGURE 9 shows its function in the process planning.

Firstly, the physical entities such as machining parts, processing equipment and data acquisition equipment are modeled. In this way, the configuration of processing parts, processing equipment and intelligent gateway are completed to form a physical space architecture. Secondly, with the help of 3D visualization software and simulation software such as Plant Simulation, the mapping physical space of digital twin virtual body is established and multi-dimensional modeling is completed. Among them, 3D geometric model is the basis, including geometric relations and geometric dimensions. The processing capability information, operation performance information, process behavior information, fault disturbance information, machining process reasoning rule information and simulation information of the processing equipment are divided by separate modules, and unified modeling is carried out by unified parametric definition. With the initial state of 3D model behavior visualization, the dimension model of specific module is displayed through interactive selection, and finally the multi-dimensional fusion simulation of machining process, which is multi-disciplinary, multi-modal and multi-scale ‘‘geometry-physics-behavior-rule-constraint’’ is realized.

The DTPM of machining products is an important basis for process template formulation and design departments to control the processing resources. DTPM is a complex model that integrates product lifecycle data. The on-site real-time data and simulation data have a very high guiding significance for the follow-up actual processing. The state of process resources and equipment, the state of processing parts, the process parameters, environmental parameters, equipment parameters, personnel parameters and the predicted data from simulation results directly affect the subsequent processing. Based on the DTPM constructed by DT data, the customization and modification suggestions of process template are made. Then, the modification opinions are transmitted to the design department for decision-making, and the real-time monitoring, prediction, design and modification of the process are carried out in combination with the DTPM.

B. COMPARISON BETWEEN DTPM AND TRADITIONAL PM

The traditional MBD process model that expresses product definition information is deepened into a DTPM by combining real-time data and simulation data. A process model based on digital twin is defined to solve the problem of interaction between existing process model data and actual processing field data. DTPM integrating real-time acquisition of processing data, simulation data, process information, process

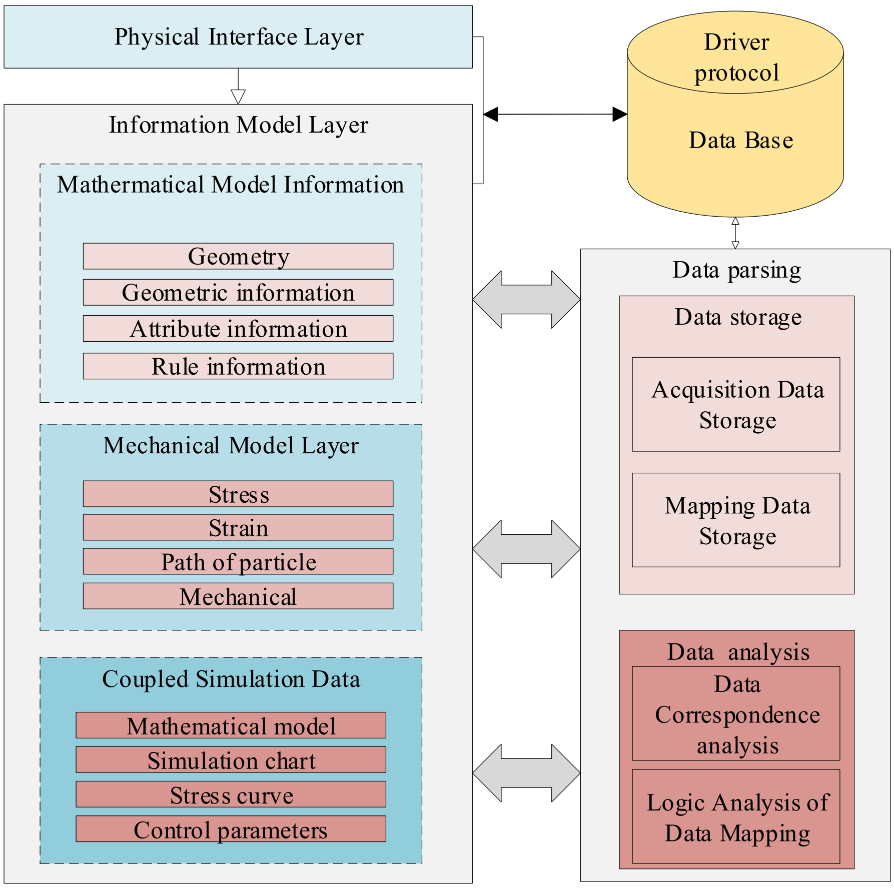


FIGURE 8. Mapping strategy for creating DT data.

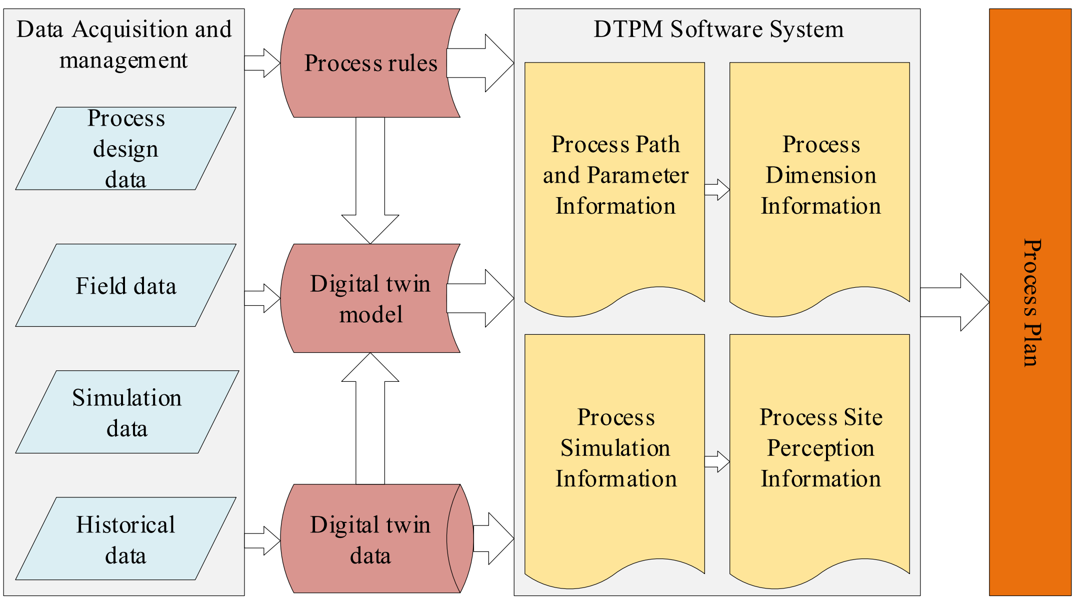


FIGURE 9. Process planning based on DTPM.

knowledge and design model is established. Determine the influence of DTPM on the overall process flow, the actual impact on subsequent process decision-making and process template.

DTPM is a multi-dimensional virtual model. It no longer only depends on design model and rigid process information. It not only demonstrates a high-fidelity visual scene for physical space, but also provides a virtual simulation based on

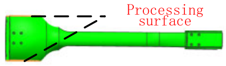
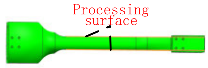
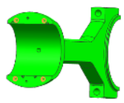
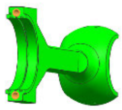
Num	Process name	Process model	Machine name
05	Turning end face		Horizontal lathe
15	Milling large end face		Gantry milling machine
30	Flat face of milling rod body		Gantry milling machine
75	Milling large end bearing groove		Machining center
80	Drilling small-end Huff face		Machining center
85	Drilling screw hole		Machining center

FIGURE 10. The key machining processes of the diesel engine connecting rod.

field data. In the process of process execution, it realizes real-time monitoring, simulation, prediction and feedback, that is, the monitoring of manufacturing physical space, the simulation of machining production line, the prediction of processed product quality, the feedback of process design department and processing site.

Taking the processing process of a part as an example, the real-time parameters and performance data of the processing equipment, such as power, tool speed, processing temperature, etc., can be visualized through the DTPM system platform, so as to better ''discover and repair''. The system guides the construction and system adjustment of the physical factory through the production performance indicators of the virtual space. Through inspection and test, the system can quickly find problems and feed back to DTPM so as to guide actual production. DTPM is a multi-disciplinary coupling integrated model. From the whole process of product design to manufacturing. Control system of DTPM relies on real-time data collection and virtual simulation data, through data transmission to complete the coordination of design and manufacturing.

The new concept of process model based on digital twin solves the problem of data island among process information, process model and equipment resource association, and proposes a data mapping mechanism that integrates human, machine and material. The data acquisition device is used to complete the field data acquisition. Data transmission protocol is used to realize integration, transmission and sharing of the data. Massive data are used to establish the DTPM. The DTPM is used to guide the process planning. The process of process planning can effectively utilize process knowledge, process information and realize real-time data interaction with the field, which provides a reliable support for the downstream process. Finally, the concurrent design of actual processing and collaborative design can be realized, the amount of subsequent modifications can be reduced, the process execution and production efficiency can be improved and the product manufacturing cycle can be shortened.

VI. CASE STUDY

The large volume of key parts, the complex processing the limited resources, high requirements of processing equipment and the high requirements of surface assembly accuracy determine that the data in the processing, such as equipment status, tool status and workpiece status, have an important impact on the quality of product processing. Technological errors, quality failures and equipment losses caused by real-time data are not permitted because of bringing burden to production efficiency, product quality and processing cost. It is very meaningful to get the solution of using real-time data in product design, building a highly integrated process model using MBD technology to guide processing and manufacturing. Therefore, process planning driven by DTPM is carried out to improve the executability of key parts processing

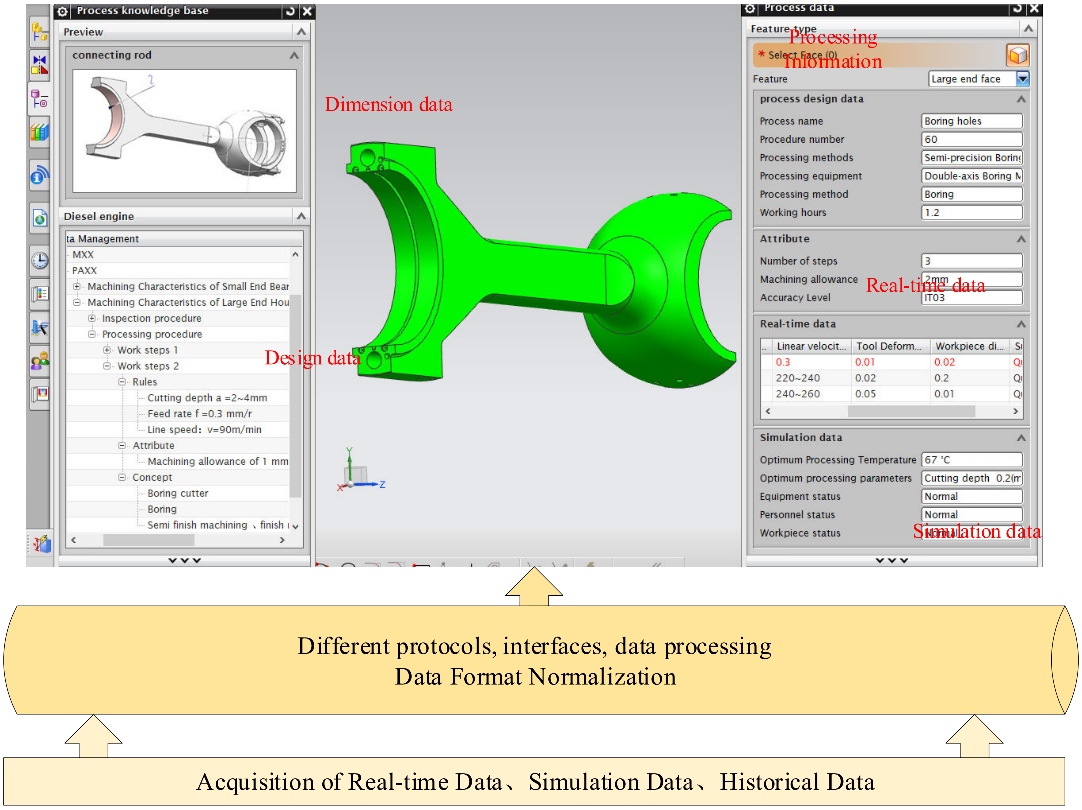


FIGURE 11. The data management method for the connecting rod.

technology of marine diesel engine and reduce the number of temporary adjustments of process. DTPM provides technical support for the transformation of new mode of intelligent manufacturing.

A. DESCRIPTION OF EXPERIMENTAL OBJECTS

In order to demonstrate the effectiveness of the proposed method, the diesel engine connecting rod body is taken as an instance. It is a small batches complex part and involves 31 processes,17 of which are machining processes. For the machining processes, more than 5 machines are selected. The corresponding relationship between the key processes and machines is shown in FIGURE 10.

B. ACQUISITION OF REAL-TIME DATA AND SIMULATION DATA

DT data includes design data, process perception data, process data, historical data, and simulation data. Among them, real-time processing data and simulation data of workpiece, equipment and environment are the key. Real-time data is acquired by intelligent sensing equipment such as sensors; simulation data is acquired through simulation software and algorithm optimization; process design data is acquired from the established process knowledge base. In order to realize the process planning and DT modeling of workpiece processing, it is necessary to establish organization and management methods of all data.

Taking the connecting rod of diesel engine as an example, the data management method is shown in FIGURE 11. The acquisition and management process of real-time data is divided into four steps: (1) Identifying static information (such as attributes of process equipment and basic attributes of workpiece) by using RFID tags and bar codes. (2) Obtain dynamic information based on multi-intelligent sensors (such as laser rangefinder, infrared rangefinder, etc.) and monitoring system (such as displacement monitoring system, task management system, etc.) (such as machine tool operation parameters, workpiece geometry and shape, process execution data). (3) Establishing data transmission network based on interface protocol to ensure efficient transmission and fusion of real-time data. (4) Use database software to store, manage and call all data. Another case is shown in FIGURE 12.

The acquisition process of simulation data is divided into four steps: (1) Determining simulation and optimization objects, such as processing parameters and equipment allocation status; (2) Selecting simulation software and optimization algorithm allocation operation; (3) Establishing data transmission network based on interface protocol to ensure efficient transmission and fusion of real-time data. (4) Use database software to store, manage and call all data.

In order to verify the validity of DTPM, the connecting rod of diesel engine is selected for test on the basis of the developed system. The results clearly show the capability

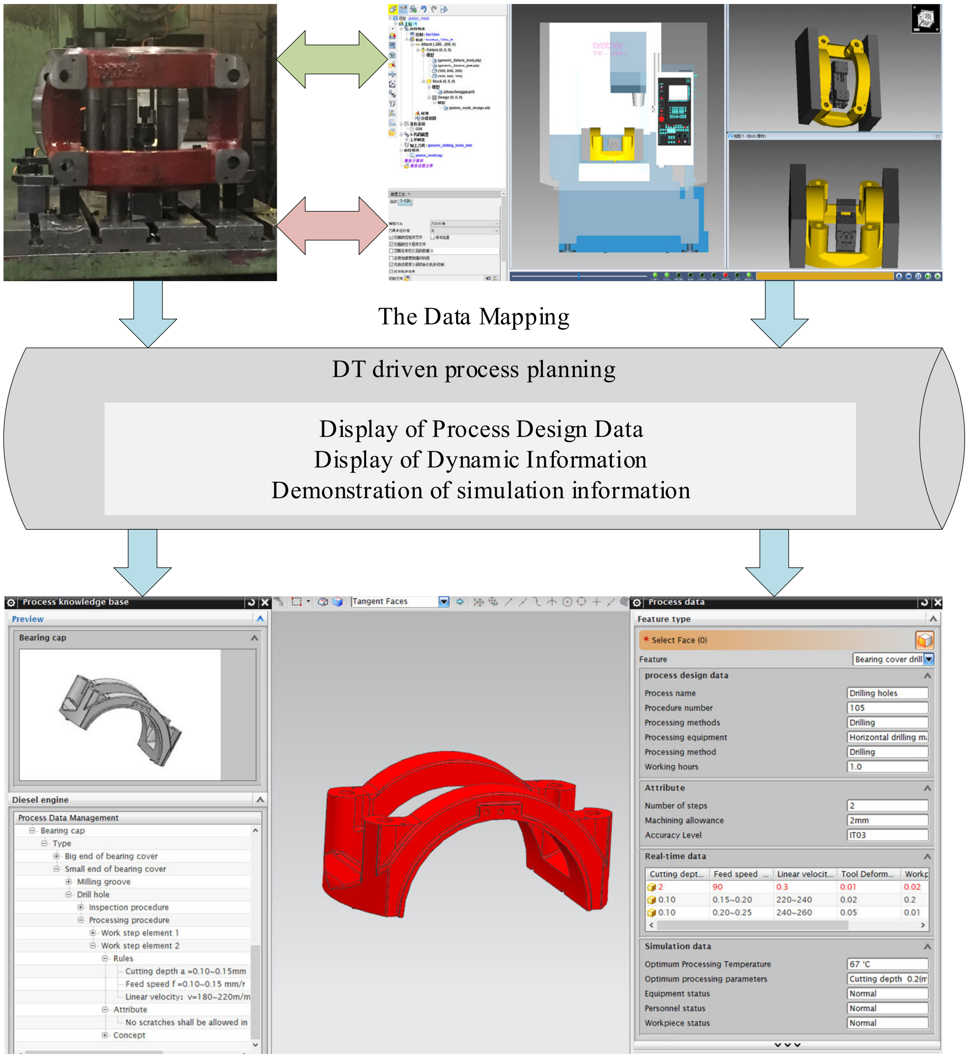


FIGURE 12. The application case.

of the method, and the implementation process is described in FIGURE 13. Firstly, data acquisition, fusion and further generation of DT data are carried out. Secondly, DT data is used to drive the establishment of process model, and then process executability is obtained from process model, which ultimately guides the production of physical workshop.

C. DISCUSSION

In the manufacturing workshop, if the process equipment fails, the number of workpiece processing increases or the task is temporarily increased, the process plan needs to be modified, which will take a lot of time. In order to track the process implementation of 200 connecting rods (31 manufacturing processes per link), these connecting rods are divided into 10 batches. The key process of connecting rod is shown in FIGURE.10. Tracking results show that more than 25 processes need to be modified or delayed due to emergent commands and machine maintenance. The modification or delay takes at least 18 hours, including process modification time and process delay time. In 35 modification processes, 5 processes were modified by emergency orders, resulting in waiting time exceeding 6 hours; 30 processes were modified by machine maintenance, which required more than 15 hours, including process change time of more than 6 hours and waiting time of more than 9 hours. However, using DT-driven process design evaluation method, only five processes have been modified due to emergency commands. The cost of reconstruction is less than 1.5 hours. Other process change activities are completed before process release based on real-time data of process equipment.

The results of comparison among this method and traditional diesel engine connecting rod process design method and MPD method [44] can be analyzed. It can be seen from this table that compared with traditional methods, the process execution rate has increased and saved about 20 hours. Compared with MPD method, the process execution rate saved about 2 hours.

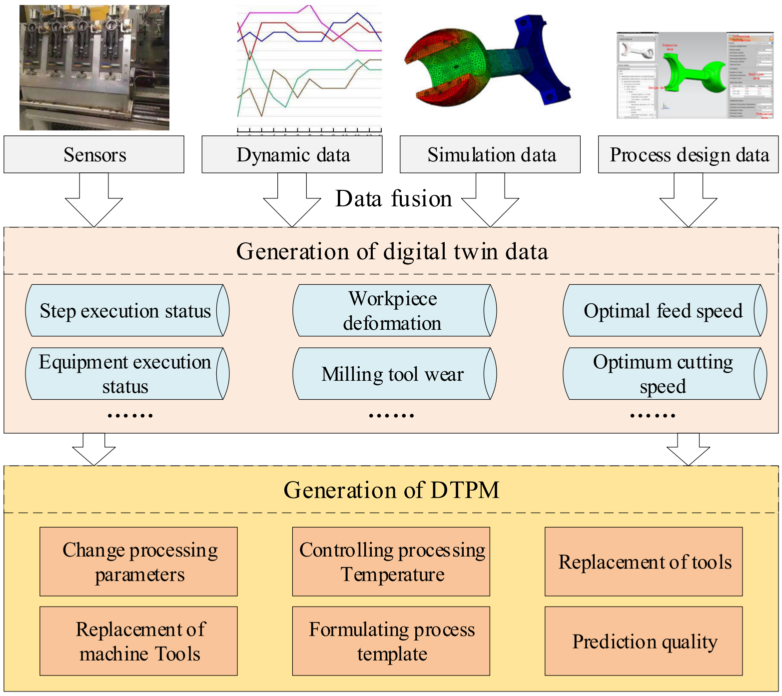


FIGURE 13. The implementation process of DTPM.

Compared with previous methods, this method has many advantages. Firstly, due to the further shortening of latency waiting time, the process execution rate is further improved. Secondly, with the acquisition and timely arrangement of the real-time status of the equipment, the utilization rate of the equipment has increased significantly. Thirdly, the integration of simulation data makes the process planning more scientific and reasonable, and reduces the possibility of failure. Fourthly, the DTPM unified expression of all the information in the processing process, which is helpful for the transmission and maintenance of manufacturing information. With the application of DTPM, the discrete model with multi-source data has been integrated. The visualization level of real-time data and simulation data with guiding significance has increased. The monitoring and control of actual processing has been further enhanced through the system platform, and the effectiveness of production has been further strengthened.

VII. CONCLUSION

In conclusion, process model has become more and more important in process planning. In view of the changeable and complex state of the processing process and the unpredictable events in real-time production, the establishment of a DTPM that can guide the process planning is an important basis for product processing and other activities (e.g. quality inspection, knowledge reused, etc.). DT integrates the data of physical space and virtual space to ensure the correct implementation of process planning, the correct formulation of process templates and the correct implementation of downstream processes. Therefore, DTPM-driven the process design is innovative.

The purpose of this study is to discuss and validate DTPM-driven machining process design. At present, this research is still in its infancy, and a lot of work is needed to improve and enrich the modeling and adaptability of process planning. It is necessary to accumulate more knowledge in design and manufacturing, improve the historical operation data and process knowledge base, and constantly reuse and improve them. By increasing the layout of sensors or more data acquisition devices, we need to collect more and more accurate real-time data. We need to make use of more subject simulation to make the prediction data more accurate and more reasonable. What's more, establishing a more complete data mapping mechanism to achieve effective mapping between process data acquisition and process design data, and provide data basis for DT database is necessary. Finally, improve the management and application of DT database, so that data can be transmitted and shared in a deeper level.

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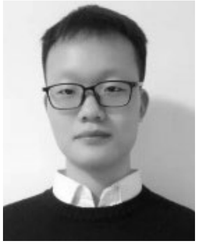

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