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Digital Twin Modeling Enabled Machine Tool Intelligence: A Review

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Abstract

Machine tools, often referred to as the "mother machines" of the manufacturing industry, are crucial in developing smart manufacturing and are increasingly becoming more intelligent. Digital twin technology can promote machine tool intelligence and has attracted considerable research interest. However, there is a lack of clear and systematic analyses on how the digital twin technology enables machine tool intelligence. Herein, digital twin modeling was identified as an enabling technology for machine tool intelligence based on a comparative study of the characteristics of machine tool intelligence and digital twin. The review then delves into state-of-the-art digital twin modeling-enabled machine tool intelligence, examining it from the aspects of data-based modeling and mechanism-data dual-driven modeling. Additionally, it highlights three bottleneck issues facing the field. Considering these problems, the architecture of a digital twin machine tool (DTMT) is proposed, and three key technologies are expounded in detail: Data perception and fusion technology, mechanism-data-knowledge hybrid-driven digital twin modeling and virtual-real synchronization technology, and dynamic optimization and collaborative control technology for multilevel parameters. Finally, future research directions for the DTMT are discussed. This work can provide a foundation basis for the research and implementation of digital-twin modeling-enabled machine tool intelligence, making it significant for developing intelligent machine tools.

Keywords Machine tool, Digital twin, Smart manufacturing, Synchronization

1 Introduction

1.1 Overview and Analysis of Machine Tool Intelligence

Smart manufacturing has become inevitable in the global manufacturing industry. Major developed countries have sequentially unveiled national strategies aimed at fostering the innovative evolution of the manufacturing industry toward smart manufacturing. The United States proposed the "National Advanced Manufacturing Strategy," Germany proposed the "Industry 4.0 Strategy" and "National Industrial Strategy 2030," and Japan proposed the "Industrial Value Chain Reference Architecture." As the core of the new scientific and technical revolution, smart manufacturing is identified as the main direction of "Made in China 2025," aiming to accelerate the development of the manufacturing industry from automation and informatization to digitalization-networked-intelligence [1, 2].

Considered "mother machines" in the manufacturing industry, machine tools are crucial in smart manufacturing. Improving the intelligence of the machine tool industry and developing intelligent machine tools have become the unanimous choices for developed countries in the machine tool industry [3]. The rapid development of emerging technologies such as new-generation artificial intelligence (AI), industrial big data, and the industrial internet has provided key technological support for machine tool intelligence. The deep integration of emerging technologies and machine tools is regarded as an

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important direction for seizing the commanding heights of competition in intelligent machine tools.

Machine-tool intelligence has attracted significant interest from researchers. The concept of a new-generation intelligent NC machine tool was introduced, and the functional characteristics of intelligent machine tools were elaborated upon. Self-healing is an important property [4]. The development of machine tools was divided into four stages: Machine tool 1.0, machine tool 2.0, machine tool 3.0, and machine tool 4.0. By discussing the typical features of intelligent machine tools, including cyber-physical systems and horizontally and vertically integrated machine tools, it was emphasized that machine tool 4.0 represents an intelligent machine tool in the era of Industry 4.0 [5]. To develop machine tools in the era of Industry 4.0, the concept of a self-optimizing machining system was proposed, which included the category of intelligent machine tools and clarified their ideal functional characteristics of intelligent machine tools [6]. By analyzing the development of machine tools and the evolution of key technologies, intelligence was discovered to be one of the main development directions of machine tools. Perception, interconnection, learning, decision-making, and self-adaptation are the main functional characteristics of intelligent machine tools [7]. These studies propose the concept of intelligent machine tools, expound on their functional characteristics, and provide a reference for machine tool intelligence.

A fog-computing-based cyber–physical machine tool system was proposed in which the physical entities of the machine tool, cyberspace, and human beings were closely connected through the technologies of perception, calculation, interaction, and control. The collaboration and intelligence of machine tools have significantly advanced [8]. Based on the three paradigms of smart manufacturing, the development of machine tools from NC machine tools through Internet + machine tools to intelligent machine tools was systematically expounded. The deep integration of new-generation artificial intelligence and manufacturing technology has been verified as an effective method for developing intelligent machine tools [9]. A conceptual framework for cyber-physical machine tools was proposed, and key research directions and challenges were discussed [10]. The aforementioned studies explored the implementation methods of intelligent machine tools and provided technological support for developing intelligent machine tools.

As the "brain" of machine tools, the NC system is the core driving force for the intelligent development of machine tools. A cloud control system for intelligent machine tools that combines cloud computing and machine tool control was proposed by analyzing the development and existing problems of machine tool control systems [11]. An intelligent control system architecture for machine tools was proposed, and the key technologies of the intelligent control system were discussed. Intelligent control systems have also boosted the development of machine tools [12].

Based on the above research, we believe that an intelligent machine tool is a high-performance NC machine tool with functional characteristics, including self-perception, self-learning, self-decision, self-execution, self-adaptation, and data and network, as shown in Figure 1. Self-perception means that intelligent machine tools can autonomously perceive multisource heterogeneous data during operation, including displacement, speed, current, voltage, cutting force, and vibration. Owing to the underlying evolution of machine tool performance, such as machining precision and dynamic behavior, the perceived data can be processed, analyzed, and trained to obtain data-based models in self-learning using data preprocessing, data fusion, and machine-learning techniques. The obtained models and online data provide the foundation for self-decision. Combined with condition monitoring, fault diagnosis, performance prediction, and parameter optimization, the machine tool performance can be dynamically predicted, and decision-making and optimization instructions are formed. Based on the instruction data, the operation process of intelligent machine tools can be autonomously controlled during self-execution using technologies such as intelligent interpolation, servo tuning, and error compensation. Intelligent machine tools, equipped with historical and real-time data, data-based models, and data for decision-making and execution, can adapt to variations in processing conditions and machine tool states. This adaptability covers changes in pose and load, tool wear, and machine failure, allowing intelligent machine tools to maintain high performance. Data and networks refer to the data interactions among the five parts through networks. Based on data interaction, intelligent machine tools can realize interconnection with hardware and software and two-way interaction with virtual models, such as horizontal, vertical, and virtual-real interconnections.

1.2 Origin and Development of Digital Twin

1.2.1 Origin of Digital Twin

The concept of twins first appeared in the National Aeronautics and Space Administration (NASA) [13]. In this project, NASA built two identical aircraft, and the one that remained on Earth was called a twin. In various stages, such as flight preparation and mission execution, the twin reflects and predicts the spacecraft states through flight training and simulation experiments and assists astronauts in making correct decisions

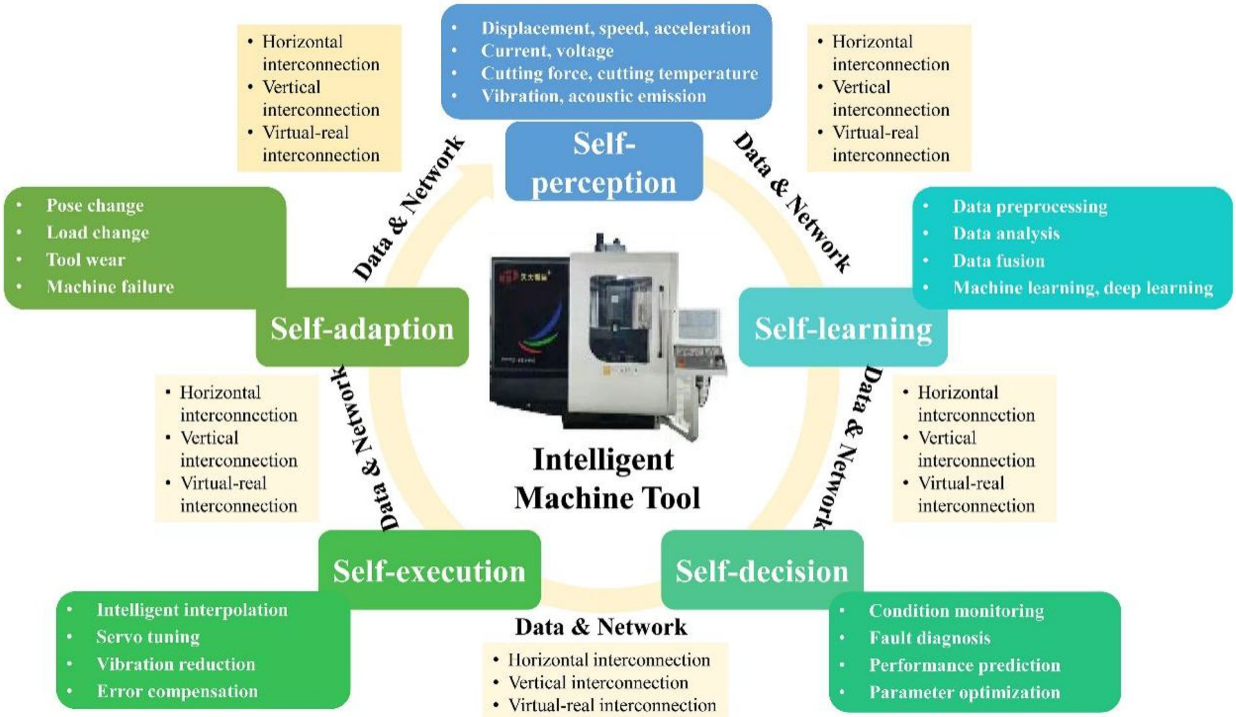

Figure 1 Intelligent machine tool

during mission execution. At this point, a twin is a physical entity.

The digital twin prototype was first proposed by professor Grieves in 2003 and was called a virtual digital representation equivalent to a physical entity. It is defined as a digital replica of a specific device or group of devices. It can abstractly represent real devices and be used as a basis for testing under real or simulated conditions. Although this concept was not currently called a digital twin, it had the main components of a digital twin, namely the physical space, virtual space, and data interface between the two [14]. Currently, the twin evolves from a physical entity into a digital twin in a virtual space.

The concept of digital twins did not initially attract attention. In 2011, digital twins ushered in new development opportunities. In 2011, the Air Force Research Laboratory (AFRL) of the United States proposed the concept of a digital twin for the maintenance and life prediction of aircraft under complex service environments. The concept of "airframe digital twin" was proposed in 2012 [15, 16]. In the same year, the AFRL and NASA jointly proposed building a digital twin for a future aircraft. A digital twin is defined as a highly integrated multiphysics, multiscale, probabilistic simulation model for an aircraft or systems. It can adopt physical models, sensor data, and historical data to reflect the real-time states of flight entities [17]. Additionally, in 2012, NASA released a roadmap titled "Modeling, Simulation, Information Technology, and Processing," officially introducing the concept of the digital twin to the public domain [18]. The proposal of the digital twin concept is considered by researchers in the aerospace industry as one of the pioneering studies on AFRL and NASA. This was used as a reference to conduct application research on digital twins in the aerospace industry.

1.2.2 Development of Digital Twin in Manufacturing

Considerable attention has been paid to the in-depth implementation of digital twins in aerospace, expanding from aerospace to energy, manufacturing, and other fields. In manufacturing, the digital twin appeared earlier in research on predictive manufacturing systems in 2013. The digital twin was a coupled model of an equipment entity running on a cloud platform, which can use a data-driven algorithm and integrated knowledge of physical mechanisms to simulate and analyze the health status of the equipment entity [19]. In 2014, a digital twin was introduced to study the crack propagation paths in machined parts. The crack propagation path of a part was predicted based on changes in the geometric dimensions during machining. This feature is the core of the part digital twin [20]. Since then, research on the digital twin in manufacturing has mainly been divided into two categories: The digital twin of manufacturing systems and products.

In digital twin manufacturing systems, the concept of an experimental digital twin is proposed by combining a virtual test bench with a digital twin. A digital twin model of a factory is established to guide the movement of workers and robots [21]. The concept of a digital twin workshop is proposed, and the system composition, operation mechanism, four characteristics, and five key technologies of the workshop are expounded. The basic theory and key technologies for realizing the cyber–physical fusion of DT workshops are discussed considering the four dimensions of physical fusion, model fusion, data fusion, and service fusion. This study provides a theoretical reference for implementing a digital twin in a manufacturing workshop [22]. Since then, research on the digital twin in manufacturing systems has grown exponentially.

The application modes and architectures of digital twins in various scenarios have been explored, including the intelligent management and control of manufacturing workshops [23, 24], dynamic scheduling and optimization of production processes in workshops [25–27], and design and commissioning of production lines [28–30]. Modeling methods and technologies for digital twins in workshops have also been studied [31–34]. To address the modeling requirements and bottlenecks of digital twin workshops, a five-dimensional digital twin model was proposed, which includes a physical entity, virtual entity, twin data, service, and connection [35]. The aforementioned studies provide a theoretical, methodological, and technical basis for the intelligent development of manufacturing workshops. Digital twins are considered a key technology for achieving the intelligence of manufacturing workshops.

In the digital twin of products, the connotation and architecture of a product digital twin was proposed and its implementation approaches in the design, manufacturing, and service stages were presented [36]. A comprehensive reference model of a product digital twin was proposed and its application to the management of product geometry changes during the design and manufacturing phases was discussed [37]. Methods for digital twin-driven product design, manufacturing, and services have been proposed, with their frameworks and implementation strategies detailed through specific case studies [38]. These studies provide a theoretical and technical reference for the application of a digital twin at various stages of the product life cycle. Since then, research on the application of digital twins in three stages of the product life cycle has been conducted: Product design and optimization [39, 40], product processing and assembly [41–43], and product maintenance and service [44, 45].

This model is the basis for completing the aforementioned application studies. Therefore, various modeling methods and technologies for producing digital twins have been studied [46–49] to achieve the synchronous symbiosis of products in digital and physical spaces and improve product intelligence.

1.3 Correlation Analysis between Machine Tool Intelligence and Digital Twin

Digital twins have become key technologies in smart manufacturing. Machine tools are the basis for intelligent development in the manufacturing industry, and their intelligence is closely related to digital twins.

Digital twin modeling methods mainly include mechanism-based, data-driven, and mechanism-data hybrid-driven methods. Data- and hybrid-driven modeling forms the basis of self-learning for intelligent machine tools. Bidirectional mapping includes real-to-virtual and virtual-to-real mappings. The real-to-virtual mapping implies that various types of data are perceived and transmitted to the digital space. Virtual-to-real mapping implies that decision-making and optimization instructions are sent from the digital space back to the physical space. The self-perception of intelligent machine tools provides a database for bidirectional mapping, and the data and network form its technological basis. The dynamic prediction of physical entity performance is an effective method for intelligent machine tools to make self-decisions, and active intervention in the physical entity is an effective method for intelligent machine tools to self-execute. When operating intelligent machine tools, the digital twin model maintains synchronous symbiosis with its physical entities or processes. When the state and performance of intelligent machine tools change, the digital twin model evolves accordingly, which can improve the performance of the intelligent machine tools. The synchronous symbiosis of digital and physical spaces forms the basis for the self-adaptation of intelligent machine tools.

Based on the above analysis, the digital twin is considered a key enabling technology for machine tool intelligence. Digital twin modeling is one of the most fundamental technologies.

1.4 Research Methodology

The digital twin has received extensive attention in the fields of machine tools [10] and machining [50]. However, there have been few comprehensive discussions on digital twin modeling-enabled machine tool intelligence. Therefore, this review attempts to demonstrate how the digital twin modeling technology can be integrated into machine tools to promote machine tool intelligence.

This review focuses on journal and conference articles. Literature retrieval on digital twin modeling-enabled machine tool intelligence is conducted in the Web of Science database. The first stage involved the screening of relevant papers through a keyword search. Two keyword combinations are used to retrieve papers, namely {"Digital twin" AND "Machine tool"} and {"Digital twin modeling" AND "Machining"}. Based on the above search conditions, 42 and 50 papers were obtained (accessed July 31, 2023). A total of 82 papers were obtained by combining the abovementioned studies. The second stage was to determine high-quality research related to the concept, frameworks, key enabling technologies, and case studies of digital-twin modeling-enabled machine tool intelligence, excluding research unrelated to digital twins and machine tools. Finally, 68 studies were included in the analysis. The statistics of the collected studies are shown in Figure 2.

1.5 Structure and Overview of This Review

The remainder of this paper begins with a review of digital twin modeling-enabled machine tool intelligence in Section 2, presenting the current bottleneck problems. Section 3 details the architecture and key technologies of the digital twin machine tool (DTMT). The development trends of the DTMT are discussed in Section 4. Finally, Section 5 concludes the study.

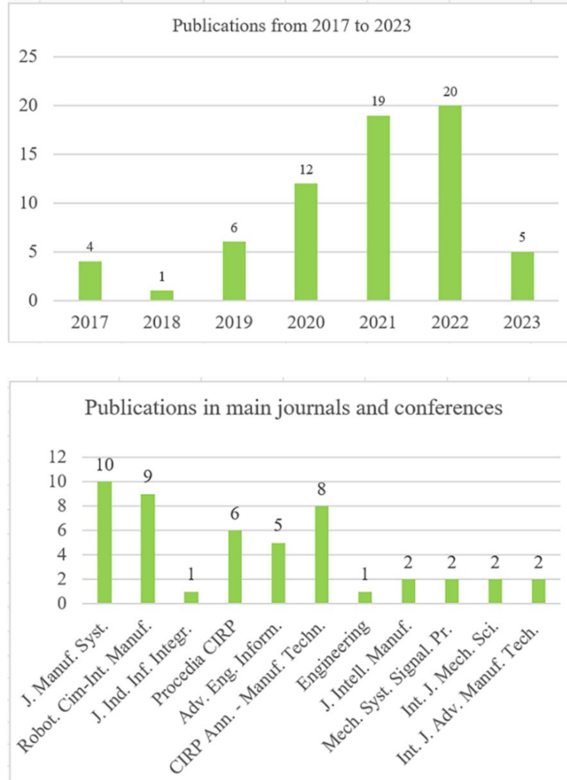

Figure 2 Statistics of collected literature

2 Digital Twin Modeling Approach Toward Machine Tool Intelligence

Digital twin modeling is considered an important bottleneck in digital twin-driven machine tool intelligence and has attracted widespread attention. Combining the six functional characteristics of intelligent machine tools, this section reviews the digital twin modeling approach toward machine tool intelligence from two aspects, including data-based and mechanism-data dual-driven approaches, and highlights the research gaps.

2.1 Data-Based Approach

2.1.1 Improvement of "Data & Network" and "Self-Perception"

A scalable and flexible database was established to store various machine tool data in a physical space, and a data-based virtual twin of the machine tool was established. Based on this, a cyber-manufacturing system with a four-layer architecture was constructed to achieve information transmission and interaction between digital and physical spaces [51]. Subsequently, the concept of a machine-tool information twin was proposed. Based on the communication protocols of MTConnect and OPC-UA, data gathering, data fusion, and information modeling were completed, and real-time interaction and feedback between the physical space, information space, and human beings were realized [52, 53]. Based on edge computing, a cyber-physical machine tool was constructed to improve the real-time data transmission and computational efficiency of the digital twin model. Long-distance perception and real-time monitoring of machine tool data during operation have also been successfully realized [54]. These studies focus on improving the "data and network" and "self-perception" of machine tools, which is foundational for other functional characteristics of intelligent machine tools.

2.1.2 Improvement of "Self-Perception" and "Self-Learning"

A biomimicry-based digital twin modeling method was proposed, and a digital twin model of the machining process of an aerospace part was established using offline and real-time data. A consistency between the digital twin model and the change in part during machining was realized [55]. Accordingly, the multiscale evolution mechanism of the digital twin model was investigated. Based on the twin data, a quality knowledge model for the machined part was established, enabling precise characterization of the machining part quality [56]. An ontology-based information-modeling method was proposed. By gathering and categorizing design data, processing data, inspection data, and other relevant data of a part, a digital twin model of the machined part was established [57]. This provides engineers with a simple and practical digital twin modeling method for machining parts.

A digital twin model for the entire lifecycle of a tool was established through the interaction and fusion of multisensor data in the digital and physical spaces. Real-time monitoring and visualization of tool status have been realized [58]. A sensor-information-based digital twin modeling method was proposed. For historical, real-time, and simulation information and delays in information transmission, the construction and adaptive systems of a digital twin were studied. With these systems, historical information is self-learned, real-time information interacts seamlessly, the semantic annotation dataset in the cloud database is processed, and the delay in data transmission is adapted. Finally, a digital twin model of an intelligent machine tool was obtained, and autonomous construction and updates of the model were realized [59].

In the research above, the collection, transmission, and interaction of various data is the specific manifestation of the "self-perception" of intelligent machine tools. The digital twin model of a machine tool or its operation process is obtained by learning the perceived data, which reflects the "self-learning" of intelligent machine tools.

2.1.3 Improvement of "Self-Learning" and "Self-Decision"

Using the data of the process parameters, tool wear, and spindle power, a digital twin model of the machining process was established, which mainly included support vector machine models in the process planning and machining preparation stages and a fully connected deep neural network model in the machining stage. The part roughness was predicted at various machining stages [60]. Based on a data-driven method, a digital twin model for the loaded contact pattern-based grinding of a spiral bevel gear was established, which primarily included a data-driven grinding simulation, contact analysis of the gear teeth, and adaptive decision-making and control. The collaborative machining of the geometric accuracy and contact performance of a spiral bevel gear was realized [61]. Based on the integration of simulation, historical, and process design data, a digital twin model of the part machining process was established to optimize the machining process [62].

An artificial neural network was trained using interpolation data and a digital twin model of the interpolation process of the machining trajectory was established to predict the feed rate curve and machining cycle time [63]. Using the command feed rate, acceleration, tool path geometry, and measured feed rate, a neural network model of each feed axis of a machine tool was trained, which is called the digital twin model. By updating the training dataset, the digital twin model was driven to update synchronously with the physical process to realize the dynamic prediction of the feed rate and machining cycle time [64]. Combined with the transfer learning theory, an adaptive reconstruction method for the digital twin model of a machining system was proposed. When the machining conditions changed, the performance of the reconstructed model exhibited certain advantages [65]. The aforementioned studies emphasize the crucial role of the digital twin in enhancing the "self-learning" and "self-decision-making" capabilities of intelligent machine tools.

2.1.4 Overall Improvement of "Self-Perception", "Self-Learning" and "Self-Decision"

By collecting and analyzing big data such as machine tool processing tasks, processing resources, and machine tool status, and mapping them with the NC code in real-time, a digital twin model of an NC machining process was established. Optimization of the processing parameters and health protection of the machine tool have been achieved [66]. Real-time data during machining were measured using sensors and a digital twin model of the machining process was established using a semantic modeling method. The cutting force and workpiece roughness were then predicted [67, 68]. The collection and processing of real-time data were completed using multisensor fusion technology, and data transmission and storage were completed using the MTConect protocol. A digital twin model of an intelligent machine tool was obtained using data fusion and information modeling technologies. Data analysis, visualization, and decision optimization were completed, providing a basis for dynamic optimization and contour error compensation of the machine tool [69].

Based on the collection and fusion of various data on thin-walled part machining, a digital twin model for the workpiece and machine tool was established. This model was employed in the machining preparation, machining, and quality inspection stages, as shown in Figure 3 [70]. Machining preparation and process monitoring were conducted, resulting in tool-path optimization and reduced deformation of thin-walled parts. The twin data were trained using a machine learning algorithm, the mapping relationship between the milling parameters and machining results was established, and the dynamic update of the digital twin model was driven by the scene-aware data. Multi-objective optimization and decision-making analysis of machining parameters were

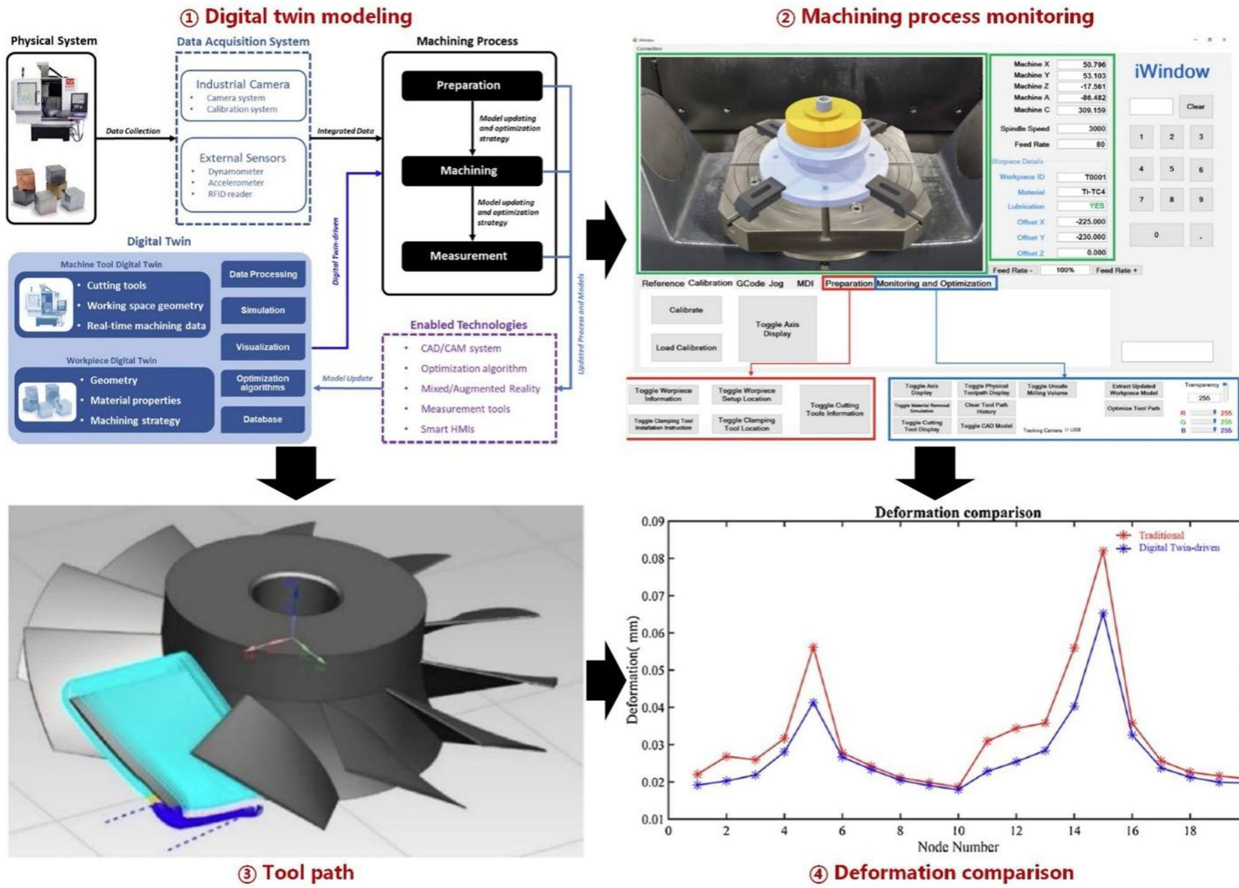

Figure 3 Digital Twin-driven machining process for thin-walled part manufacturing (Source: Adapted from Ref. [70])

performed, and real-time optimization of the machine tool was achieved [71]. A digital twin model of a dedicated machine tool was established based on standard communication protocols, such as MTConnect and OPC-UA. In this model, the spindle load and NC data were synchronized. By analyzing the historical data, the processing load was unified, the NC code was optimized, and the processing efficiency was improved [72].

Using the NC system and external sensors, multisource heterogeneous data, such as equipment, tools, and workpiece data, were collected in real-time. By classifying, correlating, and aggregating real-time and historical data, a digital twin model of the machining process was established using a data-driven method. Dynamic predictions of roughness and adaptive optimization of the process parameters were realized [73]. Based on the collected static and dynamic data, the pigeon heuristic optimization algorithm and support vector machine were combined to establish a roughness prediction model, which was the core of the digital twin model. Based on the predicted roughness, the machining parameters were dynamically optimized to ensure that the workpiece roughness constantly satisfied the requirements during machining [74]. Real-time data during the five-axis milling of thin-walled parts were measured using various sensors. The collected data were transmitted to the digital space, and a fusion of multisource heterogeneous information was performed. A digital twin model of the milling process for thin-walled parts was then obtained. Furthermore, monitoring of the machine tool status and prediction of machining deformation have been completed [75].

In the above studies, the important methods and key technologies of digital twins in machine tool intelligence were systematically studied, and the “self-perception,” “self-learning,” and “self-decision” of intelligent machine tools were achieved simultaneously. The “self-decision” includes not only the performance prediction of machine tools but also the optimization of the operation parameters and performances.

2.1.5 Overall Improvement of "Self-Perception", "Self-Learning", "Self-Decision" and "Self-Execution"

A cloud-edge collaboration-based digital twin modeling method was proposed for the thermal error control of machine tools. By collecting, transmitting, storing, and integrating multisource heterogeneous data during machining, valuable datasets were created. These datasets were used to train an enhanced LSTM network at the edge and cloud computing layers, enabling dynamic prediction of thermal errors, as illustrated in Figure 4. Compared to the other methods, the proposed method showed the best prediction performance, achieving values of 96.94% for precision and 2.5248 for the RMSE. By establishing a comprehensive machining error model, the thermal error was compensated for, and the machining error was effectively reduced, as shown in Figure 5. The fluctuation range of machining errors is [−4.0 μm, 4.0 μm] with the proposed CEDTS system [76]. Based on realizing the "self-perception," "self-learning," and "self-decision," this work realizes the thermal error control of machine tools, which represents the "self-execution" of intelligent machine tools. Similarly, DT models of intelligent machine tool swarms have been constructed based on edge computing and knowledge graph technologies. Using these models, real-time perception, high-fidelity simulation, high-confidence decision-making, and the control of machine tools in a swarm were realized and implemented [77].

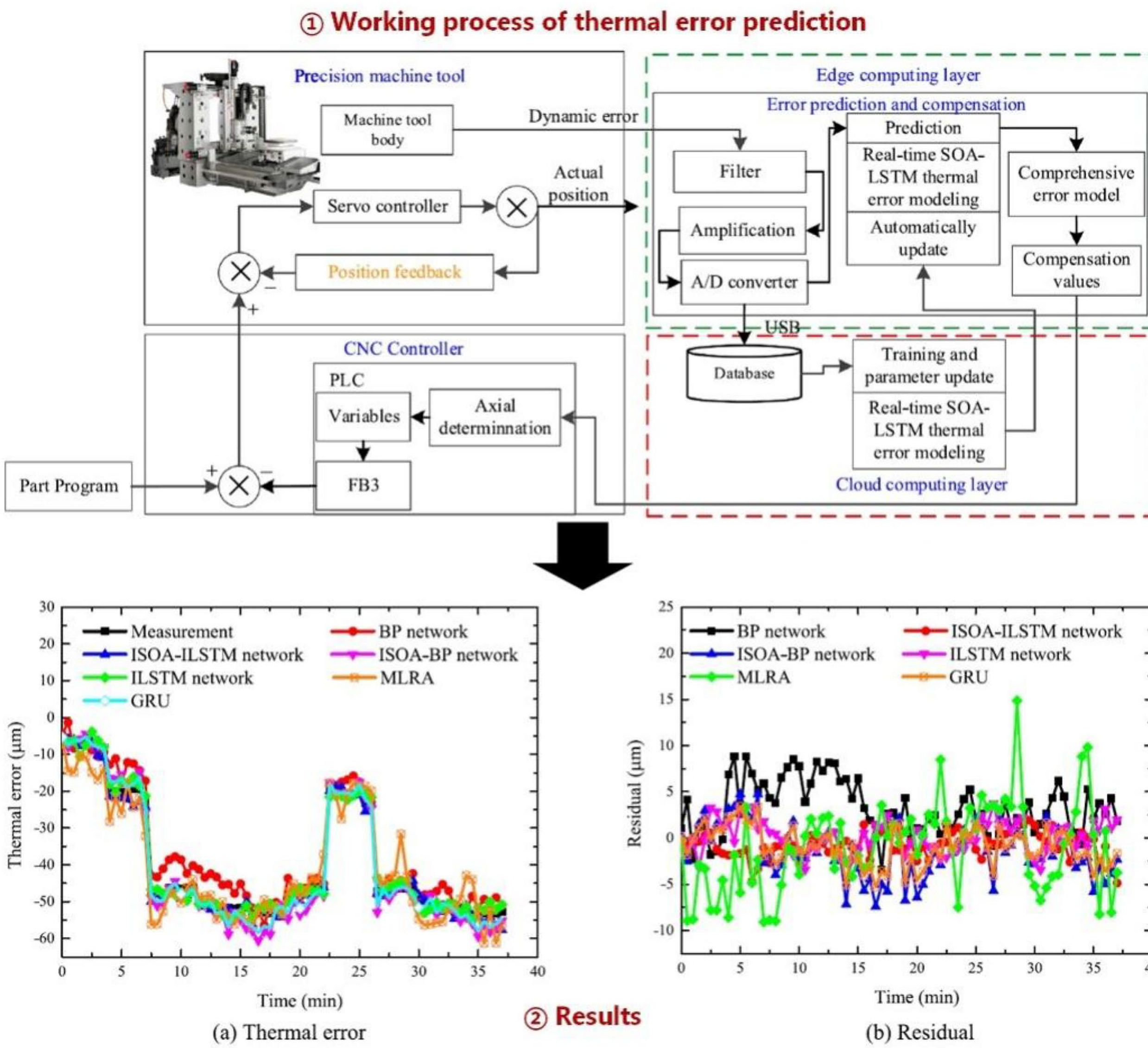

Figure 4 Thermal error prediction of machine tool (Source: Adapted from Ref. [76])

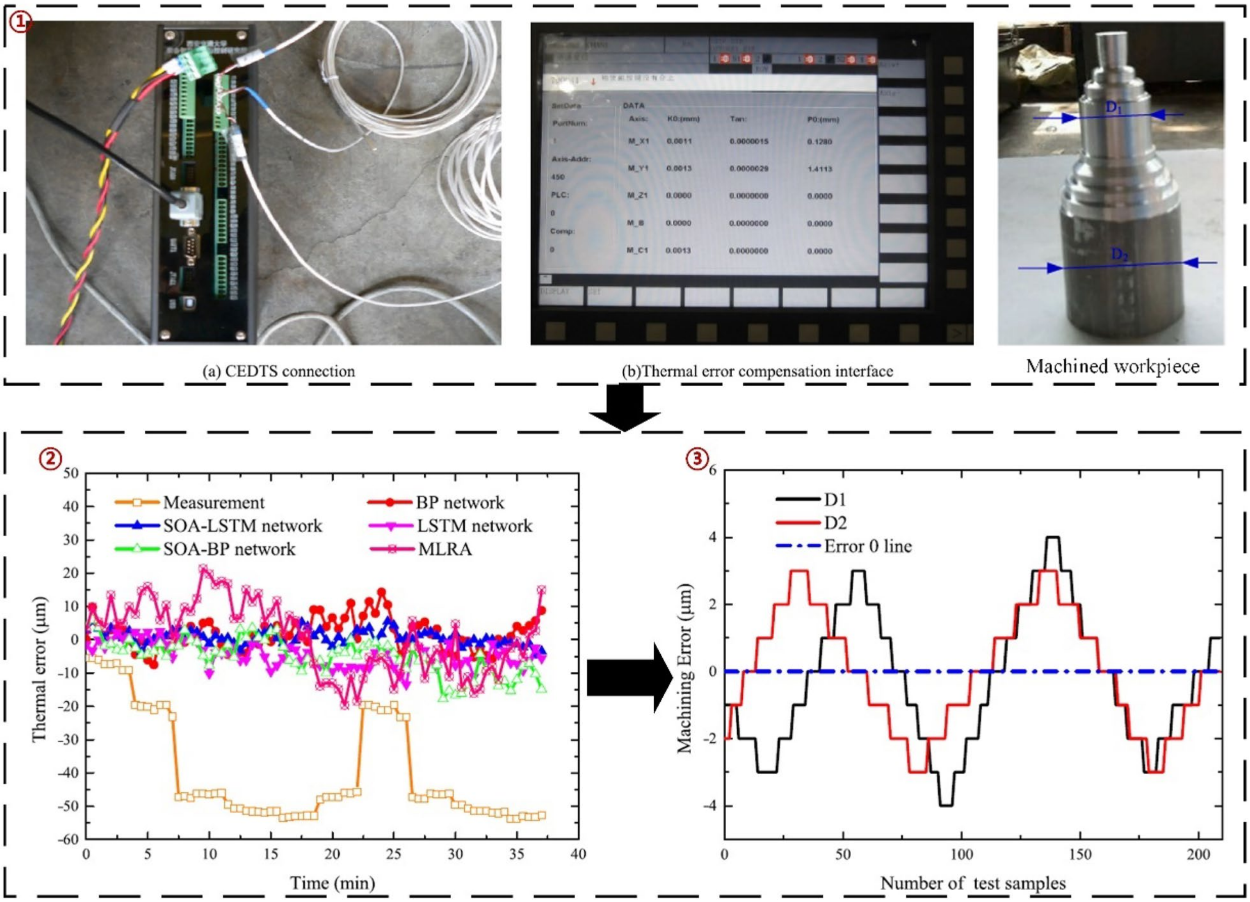

Figure 5 Machining error reduction with thermal error control (Source: Adapted from Ref. [76])

2.1.6 Summary

In the above studies, various datasets were perceived and learned, and the dynamically changing behaviors of machine tools were characterized. That is, the "self-perception" and "self-learning" of intelligent machine tools were achieved. On this basis, the real-time monitoring and dynamic optimization of the machine tool operation process were completed, which represents the "self-decision." Owing to the opaque and unexplained nature of AI [78], the inference mechanism of digital twin models constructed using data-based methods is not yet fully understood or interpretable by physics. These digital twin models are viewed as "black boxes," because of their lack of interpretability [79]. The difficulty in ensuring precise intervention during machine tool operation makes it challenging for data-driven digital twins to enable intelligent machine tools to autonomously execute tasks.

2.2 Mechanism-Data Dual Driven Approach

Compared with the data-based approach, the mechanism-data dual-driven approach has more potential for improving the interpretability of digital twin models [80]. The mechanism model depicts the physical attributes and behaviors of machine tools. For instance, a frequency response function characterizes natural frequencies [81], and a comprehensive model composed of torque commands, cutting and friction loads, and multibody dynamic equations represents position-dependent dynamic behaviors [82]. Hence, the mechanism-data dual-driven approach is increasingly being studied to construct digital twin models of machine tools to realize the functional characteristics of intelligent machine tools.

2.2.1 Improvement of "Data & Network" and "Self-Perception"

A digital twin model of the machine tool was developed in the form of software. The digital twin model was composed of CNC software, simulation software, 3D models, and data interfaces. Based on 5G technology, a two-way connection between the digital twin model and machine tool entity was built to realize the real-time monitoring of machine tool operation [83]. This research empowers machine tool intelligence through 5G technology, focusing on the "data and network."

By combining a simulation-based virtual numerical controller kernel with perceived machining data, a digital twin model of a machine tool was established, and integrated software was developed to verify the NC code syntax [84]. The characteristics and interrelations of multisource data during machining were combined to construct an information model, which was integrated with the mechanism models of the machine tool motion and cutting force to establish a digital twin model. The tool trajectory and cutting force were visualized based on the digital twin model [85]. These studies established a high-fidelity digital twin model based on the "self-perception" of intelligent machine tools. To realize "self-learning," the synchronization between the digital twin model and the physical entity is also required.

2.2.2 Improvement of "Self-Perception" and "Self-Learning"

Considering time-varying characteristics, a digital twin model of a machine tool feed drive was identified with the excitation of command signals. The digital twin model is dynamically updated with its physical entity by preprocessing the excitation signals [86]. To overcome the shortcomings of the mechanism-based machining simulation model in real-time simulations, process data were transferred from the CAM software to a machining simulation model, thereby realizing the synchronization of the command and machining simulation trajectories. A digital twin model was developed, featuring a machining simulation model that was updated dynamically. Through the collaborative deployment of the digital twin model on the edge and cloud, real-time simulations of geometry [87], cutting force, and tool wear [88] were performed. Considering the geometric changes in an in-machining workpiece, a 3D model of the workpiece and its STEP-data were integrated to establish a digital twin model for the machining process. The workpiece geometry during machining was characterized dynamically [89].

The aforementioned studies not only establish high-fidelity digital twin models but also collect various data in real-time through the "self-perception" feature of machine tools. The collected data were used to drive the synchronous symbiosis of the digital twin models with their physical entities. In other words, the "self-learning" capability of intelligent machine tools was achieved.

2.2.3 Improvement of "Self-Perception" and "Self-Decision"

(1) Monitoring of machine tool status

A digital twin model of a five-axis grinding machine was established by integrating geometric, logical, and other mechanisms and data models. Based on this, a digital twin-based monitoring system was developed, and real-time monitoring of the machine tool status was achieved [90]. An external computer with a mechanism simulation model was linked to the NC software with real-time machining process monitoring and a control model to obtain a digital twin model of the machining process. The simulated cutting force and torque were stored in a file and accessed using a real-time machining process monitoring and control system, and tool failure monitoring was realized [91]. A digital twin model of a machine tool spindle system was established, including geometric, physical, behavioral, and rule models. The digital twin model was deployed on a workstation with a database and professional software. Through the interactive fusion of the digital twin model and its physical entities, real-time monitoring of the dynamic characteristics of the spindle system was achieved [92].

These established digital twin models were mainly composed of machine–tool mechanism models. Perceived data were adopted to drive these digital twin models to monitor the states of machine tools. The monitoring is one of the most important components of the "self-decision."

(2) Prediction of machine tool performance

Sensor data and machining information were integrated to construct profiles of the machining characteristics. Using OpenGL, the machining characteristic profiles were combined with structural models to establish a digital twin model of the machine tool. Given the digital twin model, the online prediction of workpiece roughness was achieved [93]. Similarly, real-time and simulation data of the machine tools were collected and fused to develop the data models. Using algorithms such as particle filters, data models were integrated with multidomain mechanism models to obtain digital twin models. Using digital twin models, the power, torque, and cutting force of machine tools [94] and the remaining life of the tools were accurately predicted [95].

Dynamic and thermal digital twin models of the machine tools were established based on the geometry and material properties of the machine tool structure. By integrating these models, a comprehensive digital twin model of the machine tool was developed, and its parameters were identified. Using the integrated digital twin model, the thermal deformation and dynamic cutting forces were accurately predicted [96]. A digital twin model of a machine tool was established using a multidomain unified modeling method, which mainly comprised description, data mapping, and algorithm models. Based on the digital twin model, fault prediction of the machine tool was realized [97]. Based on the CNC data, a digital twin model of a machine tool was established using system identification and parameter estimation. Considering a machining center [98], gear grinding machine [99] and five-axis machine tool [100] as specific objects, the following and contour errors were predicted.

In addition, mechanism models of machine tool feed drives were established by considering nonlinear dynamic characteristics. Through the fusion of the mechanism and data models, such as a deep convolutional neural network model, digital twin models were obtained, with which the following errors [101, 102] and contour errors [103] of machine tool feed drives were accurately predicted.

These studies adopted traditional methods and machine learning algorithms to establish the mechanism and data models, respectively. Digital twin models of machine tools and their components are obtained by integrating these mechanisms and data models using theoretical formulas, unified modeling languages, or software development. Given the digital twin model, the machine tool performance was predicted. Prediction is another important component of the "self-decision."

(3) Optimization of machine tool performance

A digital twin model of the machine tool is established by integrating the mechanism and data models. These mechanism models include structural topology, multibody kinematics, and dynamics models. These data models involved a data interface model and a transfer learning model. These models were uniformly deployed into self-developed software and the process parameters were optimized [104]. Using a similar method, the feed speed of a machine tool was optimized [91]. Optimization is also one of the most important components of the "self-decision."

In the above studies, through the collection and interaction of data in digital and physical spaces, state monitoring, performance prediction, and optimization of machine tools were achieved based on the established digital twin model. This achieves the "self-decision" to a certain extent. The state and performance of machine tools vary over time during operation. The established digital twin models have not yet achieved synchronous symbiosis with physical entities or processes. The real-time prediction and optimization are difficult to achieve.

2.2.4 Improvement of "Self-Learning" and "Self-Decision"

A method for maintaining dynamic consistency between the digital twin model and the physical entity was proposed. The dynamic update of the digital twin model was driven primarily by data management, which provided a model basis for the online prediction of machine tool failure [105]. Considering the influences of servo dynamics, friction, and clearance, a digital twin model of a machine tool feed drive was identified using a particle swarm optimization algorithm. The servo parameters were optimized, and the performance degradation caused by changes in the dynamic characteristics of the machine tool was predicted online [106]. An online prediction method for machining quality was proposed based on a transferable digital twin model for the machining process, which was established through the fusion of mechanisms and data models. The mechanism and data models were integrated to develop a digital twin system for the drilling process, transfer learning theory was employed to adaptively update the digital twin model under variable working conditions, and the machining quality was predicted online [107].

Considering the dynamic characteristics of the machining process, a digital twin model for a machine tool was established by integrating the mechanism and data models. The mechanism model refers to the process correlation interaction mechanism, and the data model is considered the core driving model of the digital twin model. The digital twin model and operation process were synchronized using intermediate data. The dynamic optimization of cutting parameters and online evaluation of machining stability have been realized [108]. The Gaussian process regression algorithm was embedded in a mechanism model to obtain a surrogate model for processing thin-walled parts, which is a digital twin model. The digital twin model was calibrated by considering the uncertainties in the cutting forces and tool wear. The mapping relationship among the machining parameters, machining position, and machining error was established, and the machining errors of thin-walled parts were dynamically predicted [109]. Using a similar method and considering the in-process workpiece dynamics, the time-varying natural frequency and mode shape of a thin-walled structure during milling were dynamically predicted [110].

Focusing on time-varying behaviors during machine tool operation, these studies adopted real-time data to drive the synchronous symbiosis of digital twin models with their physical entities. This reflects the "self-learning" capability of intelligent machine tools. Based on the established digital twin model, dynamic prediction and optimization of machine tool performances are completed, which reflects the "self-decision."

2.2.5 Overall Improvement of "Self-Perception", "Self-Learning" and "Self-Decision"

A multilevel and multidomain electromechanical-hydraulic integrated digital twin model of a machine tool is established using Simscape. Mechanical, hydraulic, control and electrical submodels were employed to describe the operating mechanism of the machine tool, and data in digital and physical spaces were adopted to drive the dynamic update of the digital twin model. The virtual commissioning of servo parameters was realized based on the digital twin model [111]. A wear mechanism model of a machine tool transmission system was established based on meta-action theory, and a performance degradation model was established using a particle filter algorithm. A digital twin model of the transmission system is obtained by integrating these two models. Real-time and historical data were collected to update the digital twin model, and the performance degradation of the transmission system was dynamically predicted [112]. A multiphysics digital twin model of the gear skiving process was established using the mechanism-data dual-driven method. The dynamic consistency between the digital twin model and the gear-skiving process was driven by real-time data. A mapping relationship among the skiving parameters, cutting force, and temperature was established, and the cutting force and temperature were predicted dynamically [113]. By integrating an information model, a mechanism model, and a digital thread, a digital twin model of a CNC system was developed. Based on edge intelligence technology, the digital twin model was deployed using task partitioning and model selection algorithms. As shown in Figure 6, real-time monitoring and prediction of the tool status and wear were achieved [114].

Based on the "self-perception," the perceived data are employed to update the digital twin model to ensure its synchronous symbiosis with the physical entity, which reflects "self-learning." The digital twin model is adopted to complete the dynamic prediction and online optimization of the machine tool performance, which reflects the "self-decision" capability of intelligent machine tools.

2.2.6 Overall Improvement of "Self-Perception", "Self-Learning", "Self-Decision" and "Self-Execution"

A mechanism model of burr generation was used as prior knowledge to extract features from real-time data. A data model for burr-height prediction was established using a gated recurrent network. By integrating the mechanism and data models, a digital twin model of the drilling process was developed to realize real-time monitoring of the drilling status. The machining parameters were optimally controlled using a genetic algorithm and a nearest-neighbor algorithm [115]. A virtual model of the machine tool feed drive was established based on lumped and nonlinear parameter models. The state data of the physical entity were gathered in real-time, and a model parameter update method was proposed to achieve the adaptive synchronization of the virtual model with its physical entity. Based on this, a digital twin-driven composite control strategy was presented to improve the control accuracy of the feed drive [116]. A similar method was adopted to construct a digital twin model of a multi-axis feed drive. The synchronization of the digital twin model and its physical entity was driven by multigranularity information in digital and physical spaces. Based on the established multifactor dynamic influence relationship of the contour error, dynamic prediction was realized. A comprehensive contour error reduction method was proposed to complete the interpolation of a multi-axis feed drive system [117].

A method for controlling clamping force in the machining of thin-walled parts, driven by digital twin technology, was proposed. By combining an information model with a 3D geometric model, clamping deformation model, clamping force optimization model, and other mechanism models, a digital twin model of a thin-walled clamping system was obtained, and a digital twin-based prototype system was developed. Optimal control of the clamping force was achieved through the real-time interaction of the digital twin model with its physical entity [118]. The in-process physical and geometric data of the workpiece and machine tool were collected and integrated with a mechanism model to establish a time-varying information model, namely, a digital twin model, for the milling of thin-walled workpieces. A built-in intelligent milling software system was developed using the tool NXOpen C++ in an environment of NX UG11.0. The process parameters of the next step were optimized in real-time, and intelligent control of machining chatter and error was realized [119]. A bionic digital brain (BDB) was proposed as the intelligent core of a digital twin-cutting process (DTCP). The BDB was built with digital neurons (DNs), which output optimal control solutions in real-time to ensure demand after the corpus callosum fused the left and right brain information. A digital twin-cutting process system was developed, as shown in Figure 7, and real-time monitoring, prediction, optimization, and control of the cutting process were realized [120].

Building upon the achievements in "self-perception," "self-learning," and "self-decision," these studies convey the optimal decisions such as process parameters derived from the digital twin model back to the physical space. An adaptive control strategy is presented to control the machine tool operation in real-time. This represents the "self-execution" of the intelligent machine tools. The

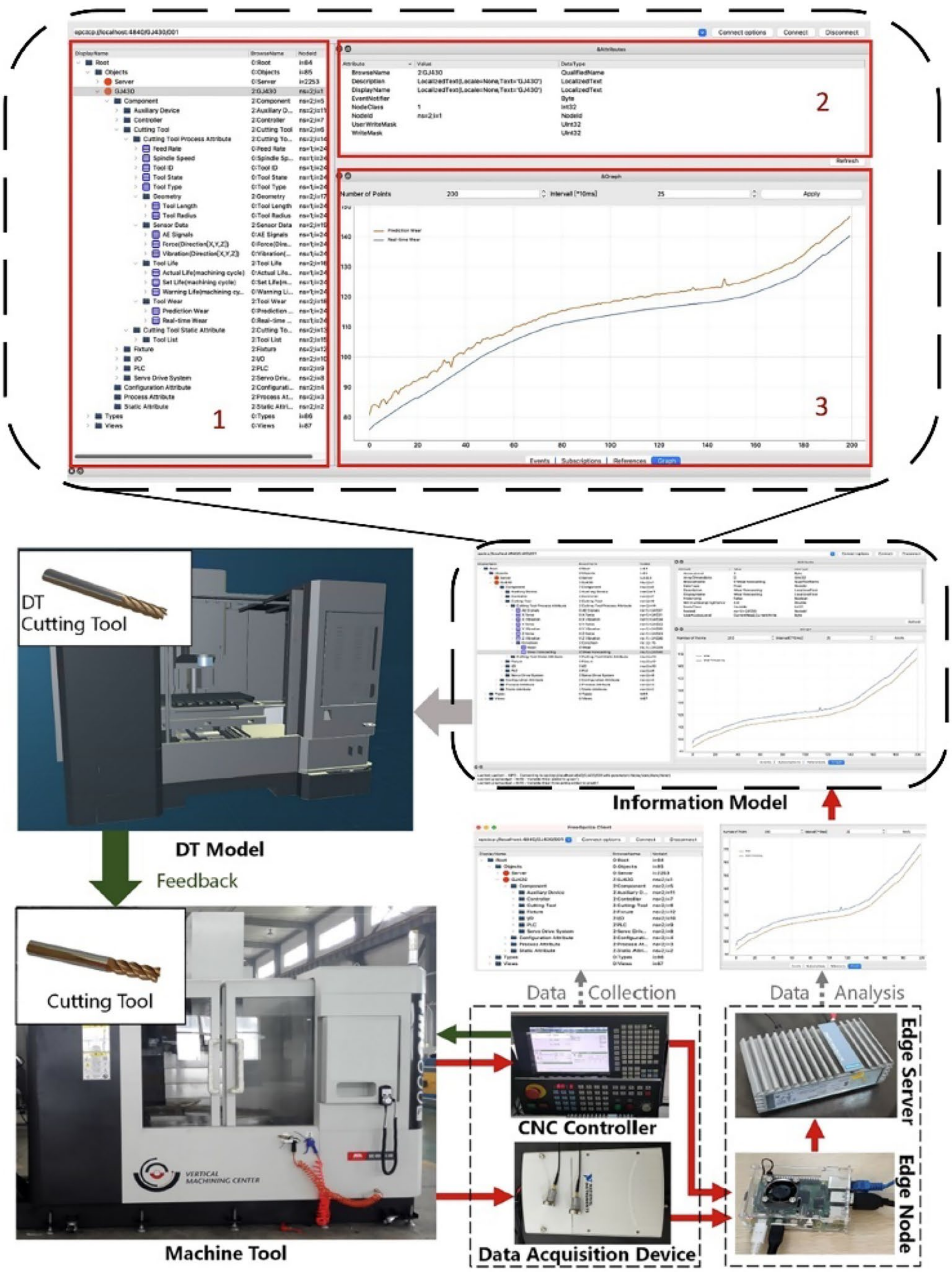

Figure 6 Edge intelligence-driven digital twin of CNC system (Source: Adapted from Ref. [114])

"self-perception," "self-learning," "self-decision" and "self-execution" capabilities are overall achieved.

2.2.7 Summary

Similar to the data-based method, the mechanism-data dual-driven method can establish a digital twin model that is synchronized with its physical entity or process and complete the state monitoring, performance prediction, and optimization of the physical entity or process. In addition, decision-making instructions can be sent back to the physical space from the digital space, the iteration and closed-loop control of the digital-physical space are formed, and adaptive control of the physical entity or process is completed. The mechanism model improves the interpretability of the model output, and the data model guarantees a dynamic

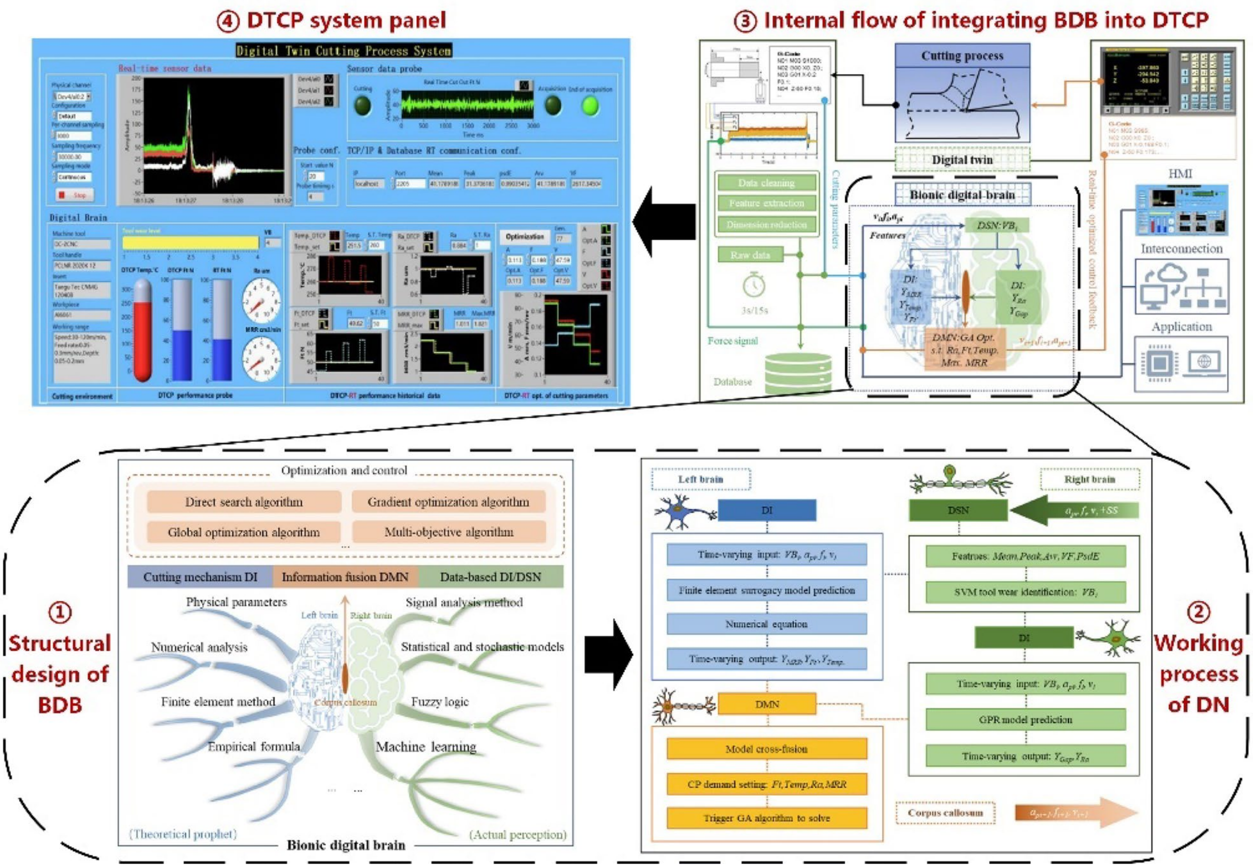

Figure 7 Bionic digital brain realizing the digital twin-cutting process (Source: Adapted from Ref. [120])

update of the digital twin model with its physical entity or process [121, 122]. Driven by the mechanism and data, the digital twin model better empowers machine tools to be intelligent, achieving "self-perception," "self-learning," "self-decision" and "self-execution."

2.3 Existing Bottleneck Problems

Compared with traditional methods, such as analytical modeling, virtual simulation, and system identification, digital twin modeling can fuse various perceived data to dynamically characterize the time-varying parameters of machine tools. In addition, it can monitor the operational states of machine tools in real-time, dynamically predict and optimize their performance, and provide complete feedback control of machine tools. The crucial role of digital twin modeling in facilitating the integration of virtual simulations with real-world operations is a significant factor in its recognition as an essential technology for advancing intelligent machine tools. However, there are still three bottlenecks in the research on digital twin modeling for machine tool intelligence.

(1) The virtual-real fusion of multisource heterogeneous data from machine tools lacks an effective method. During the operation of machine tools and their digital twin models, pose, force, deformation, vibration, temperature, and electrical data are generated in the physical and digital spaces. These data have the characteristics of various sources, sampling frequencies, magnitudes, and transmission methods and are perceived in real time using multi-sensing detection technology. Existing multisensor data fusion methods can be divided into three categories: data-, feature-, and decision-level fusion [123, 124]. In most studies on digital twin modeling of machine tools, the adopted data fusion methods belong to data-level fusion, such as Refs. [55], [58], and [59]. It is difficult to achieve high-precision, real-time, and robust virtual-real fusion of perceived data.

(2) The theoretical methods of digital twin modeling and synchronous mapping for machine tools and their operational processes are insufficient. A machine tool is a complex equipment that integrates multiple disciplines, such as machinery, elec-

tricity, hydraulics, and control. The geometry and physical properties of the entire machine and its components exhibited cross-scale characteristics. During operation, the spatial pose, load, cutting force, and dynamic characteristics of the machine tool constantly change at high speeds. A nonlinear external disturbance may excite the vibration and deformation of the machine tool at any time, resulting in a decline in the machine tool performance. Existing modeling methods make it difficult to establish a digital twin model that dynamically characterizes the machine tool performance. In addition, it is difficult to balance the high fidelity of the digital twin model with its real-time synchronization using a physical machine tool.

(3) Systematic research on real-time and collaborative control strategies for machine tool operating parameters is lacking. The operating parameters of the machine tool comprise multilevel parameters in the process, interpolation, and servo layers. The parameters of each level are coupled with each other and have a nonlinear dynamic relationship with machine tool performance. Existing research focuses on the adjustment of single-level parameters to achieve the optimal control of machine tool performance. The dynamic relationship between multilevel parameters and machine tool performance warrants further research. It is difficult to achieve real-time and collaborative control of multilevel parameters and optimal control of machine tool performance.

3 Architecture and Key Technologies of Digital Twin Machine Tool

For the bottleneck problem of digital twin modeling for machine tool intelligence, the architecture of a DTMT is proposed based on the digital twin five-dimensional model [35], and three key technologies are presented: data perception and fusion, digital twin synchronous modeling, and parameter optimization and control.

3.1 Architecture of Digital Twin Machine Tool

As shown in Figure 8, the architecture of the DTMT is composed of a machine tool entity, a digital twin model, decision and control, and data. The machine tool entity provides the mechanism and data basis for the digital twin model. The digital twin model completes the dynamic characterization of the machine tool entity and its operation process and maintains its synchronization update with the machine tool entity. Utilizing the digital twin model, the decision and control process encompasses visual monitoring, performance prediction, parameter optimization, and feedback control of machine tool operations. The data are composed of real-time data

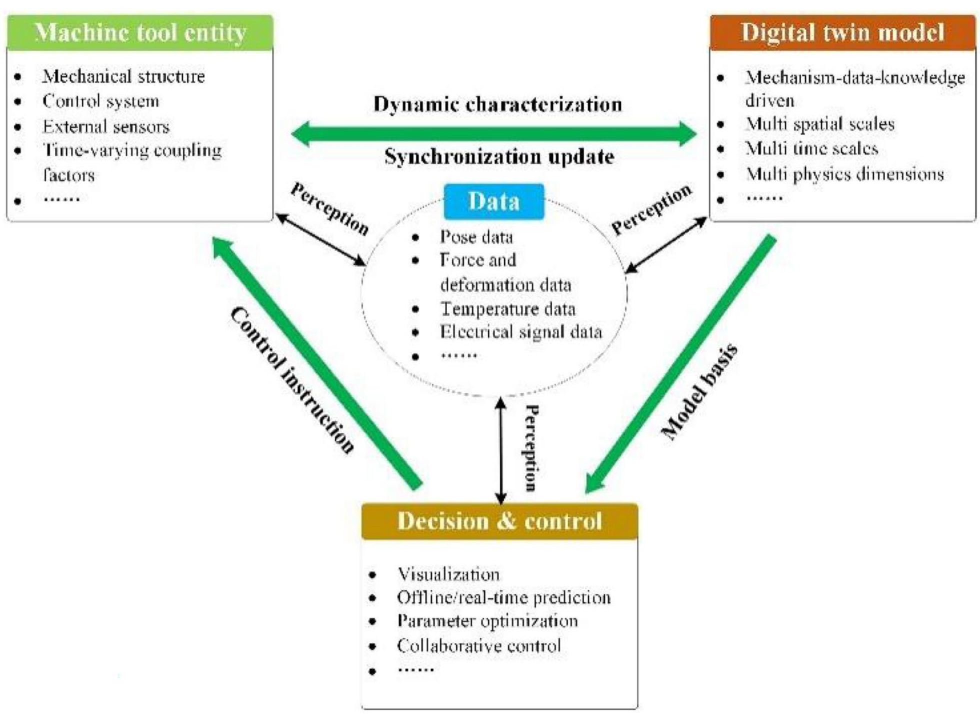

Figure 8 Architecture of the DTMT

from the machine tool entity (such as pose and electrical signal data); simulation data from the digital twin model (such as deformation and temperature data); and status, performance, and control data from the decision and control. The data not only completes the perception and fusion of multisource heterogeneous data of machine tools, but also provides an effective dataset for the machine tool entity, digital twin model, and decision and control. These four parts of DTMT interact dynamically, iterate in a loop, and form a closed loop of "perception-modeling-prediction-control" for the machine tool operation process.

The machine tool entity is composed of the mechanical structure, NC and servo systems, external sensors, and time-varying coupling factors during machine tool operation, such as the time-varying dynamic characteristics and cutting force. The mechanical structure was divided into multiple scales, including the entire machine, components, and parts. This is the specific objective of digital twin modeling. The NC and servo systems control the machine tool motion and collect pose and electrical signal data (such as the displacement of the feed axes and motor power) during machine tool operation. External sensors were employed to collect force, vibration, and temperature data. Time-varying coupling factors form the basis of the digital twin modeling mechanism. The machine tool entity provides the mechanism and data basis, executes the optimized control instruction, and is the basic carrier of the DTMT.

The digital twin model is a comprehensive digital model with multiple spatial and time scales and physical dimensions. Multi-spatial scales refer to the various spatial scales of the entire machine, components, and parts of a machine tool. Multiple time scales indicate different time scales for tracing history, characterizing the present, and predicting the future. The multi-physical dimensions represent the different dimensions of geometry, force, deformation, vibration, and motion control. This complex digital twin model must be comprehensively integrated using a mechanism-data-knowledge hybrid-driven method. Using the digital twin model, simulation data such as the deformation and temperature of the machine tool structure can also be obtained. In other words, the digital twin model dynamically characterizes the machine tool operation process, completes the synchronous symbiosis between itself and the machine tool entity, and forms the basis of the DTMT.

Decision and control were based on the digital twin model and combined with real-time data to complete the visual monitoring of the machine tool operation process. For example, the feed rate, spindle speed, and acceleration of the feed axes can be visually monitored in real-time [90]. Based on the measured and simulation data, a dynamic mapping relationship between the multilevel and performance parameters of a machine tool is established to predict the machine tool performance in real-time and offline. According to the performance prediction results, the dynamic multi-objective optimization of the multilevel parameters was completed. The collaborative control of multilevel parameters is realized, and the control instruction is sent back to the machine tool entity. Decision and control not only evolve with changes in the digital twin model and data but also complete the real-time and collaborative control of multilevel parameters during the machine tool operation. This is a complex dynamic process and is the key to successfully implementing the DTMT.

First, the data must perceive multisource heterogeneous data from the machine tool entity, digital twin model, and decision and control in real-time, and store and manage real-time data. In addition, we must fuse perceived data to form a functional dataset. The data is then sent back to the machine tool entity to control the machine tool motion, to the digital twin model to train the data model and drive the virtual-real synchronous symbiosis, and to the decision and control system to visualize the machine tool status, predict the machine tool performance online, and dynamically optimize the process parameters. Overall, the data run through all aspects of the DTMT and form its data foundation.

3.2 Key Technologies of Digital Twin Machine Tool

3.2.1 Data Perception and Fusion Technology

During the DTMT operation, multisource heterogeneous data are generated by the machine tool entity, digital twin model, and decision and control. The transmission protocols for these data include Modbus, NC Link, OPC-UA, EtherCAT, and RS485. The sampling frequency was 10–10k Hz [125]. For instance, due to restricted cache capacity, the motion control system's data collection capability constrains the sampling frequency of pose data to tens of Hertz. With the acceleration transducer, the sampling frequency of the vibration data was as high as tens of thousands of Hertz. The magnitudes of these data ranged from KB to GB, and their types included structured, semi-structured, and unstructured data. Owing to these factors, there are local, one-sided, and inaccurate problems in multisource heterogeneous data collected using existing sensing technology. Therefore, multi-protocol compatibility technology, cross-frequency sampling technology, transmission technology of multi-granularity data, and storage technology of multi-type data are needed as technical support to ensure the real-time, accurate, and two-way perception of multisource heterogeneous data in the DTMT.

Because of the above characteristics of multisource heterogeneous data, it is first necessary to perform data preprocessing on the perceived multisource heterogeneous data. The most common data preprocessing technologies used in DTMT include data normalization and data reduction. Data normalization was adopted to convert the original measured values into dimensionless values [126]. Typically used methods include min-max normalization, Z-score normalization, and decimal scaling normalization. For instance, Z-score normalization is used to regularize the spindle speed, cutting depth, feed rate, and maximum, mean, and root-mean-square values of the cutting force [113]. Data reduction is adopted to minimize the amount of data while maintaining the integrity of the original dataset as much as possible to obtain a reduced representation that is smaller than the original dataset but maintains its integrity [126]. Commonly used methods include principal component analysis, random projection, and partial least squares regression. Principal component analysis was adopted to analyze the effects of the machining and tool parameters on the cutting force and temperature. Consequently, the number of input features in the prediction model was reduced [113]. In addition, data clean (such as splitting and filtering methods) can be adopted when noisy data are generated by replacing missing data, because the data are outside the range of the measurement device [127]. Data integration should be used when different data formats from various systems, including NC systems with NC links and Internet of Things (IoT) devices with Modbus, require an exchange [128].

Second, for a sample dataset with a large deviation over time, these data are retrained to complete their learning and update, which can be performed using the deep reinforcement learning algorithm. A sample dataset with numerous features and redundant attributes was dimensionally reduced to maintain its integrity. Principal component analysis and random projection are ideal methods. In DTMT, the values of the process, interpolation, and servo parameters change slightly during a certain machining process. Real-time data on these parameters are typically limited. In this case, data augmentation methods such as virtual sample generation [129] and generative adversarial net [130], can be adopted to augment real-time data based on historical data. These technologies are collectively referred to as data update, reduction, and augmentation technologies.

Finally, according to the requirements of the machine tool entity, digital twin model, and decision and control, the classification, clustering, association rule, and prediction were performed on the dataset. These technologies are collectively referred to as data mining technologies and include artificial neural networks, deep learning, k-means methods, and regression analysis methods.

In summary, data preprocessing technology, data update, reduction and augmentation technology, and data mining technology are required as technical support to realize high-precision, real-time, and robust virtual-real fusion of multisource heterogeneous data in the DTMT.

3.2.2 Mechanism-Data-Knowledge Hybrid-Driven Digital Twin Modeling and Virtual-Real Synchronization Technology

The machine tool entity involves multiple scales, such as the entire machine, components, and parts, and includes various physical properties, such as geometric structure, statics, dynamics, and motion control. During the operation, the spatial pose, load, dynamic characteristics, and cutting force change constantly at high speeds. Nonlinear disturbances can cause the vibration and deformation of machine tools at any time. For instance, the cutting force near the resonant frequency leads to machine tool vibration [131], and the friction and inertial load can excite the vibration of the machine tool feed drives [91, 132]. The prediction and optimal control of the machine tool performance must be completed within milliseconds to ensure high efficiency, high precision, and reliable operation of the machine tool entity. Currently, achieving both high fidelity and real-time synchronization with the physical machine tool is challenging for the established digital twin model. The dynamic prediction and control of the machine tool performance within milliseconds are also difficult to complete. Therefore, digital twin modeling and virtual-real synchronization technology of mechanism-data-knowledge hybrid-driven multiscale and multidimension is proposed to provide theoretical guidance for the model construction of the DTMT.

A framework of the digital twin modeling and virtual-real synchronization technology of the mechanism-data-knowledge hybrid-driven multiscale and multidimension is shown in Figure 9. Multi-spatial scale modeling implies that the established model involves multiple spatial scales of the entire machine, components, and parts, as well as the topological relationship between models with different scales.

In the dimensions of the geometric structure, the geometric models of the entire machine tool, components (such as the feed drive and spindle system), and parts (such as the guide rail, screw, and bearing) are established to characterize the topological relationship among these components and parts. In the dimension of force and deformation, the finite element model of the machine tool, the mechanical model of components, and the cutting force model of tool tip are established to characterize

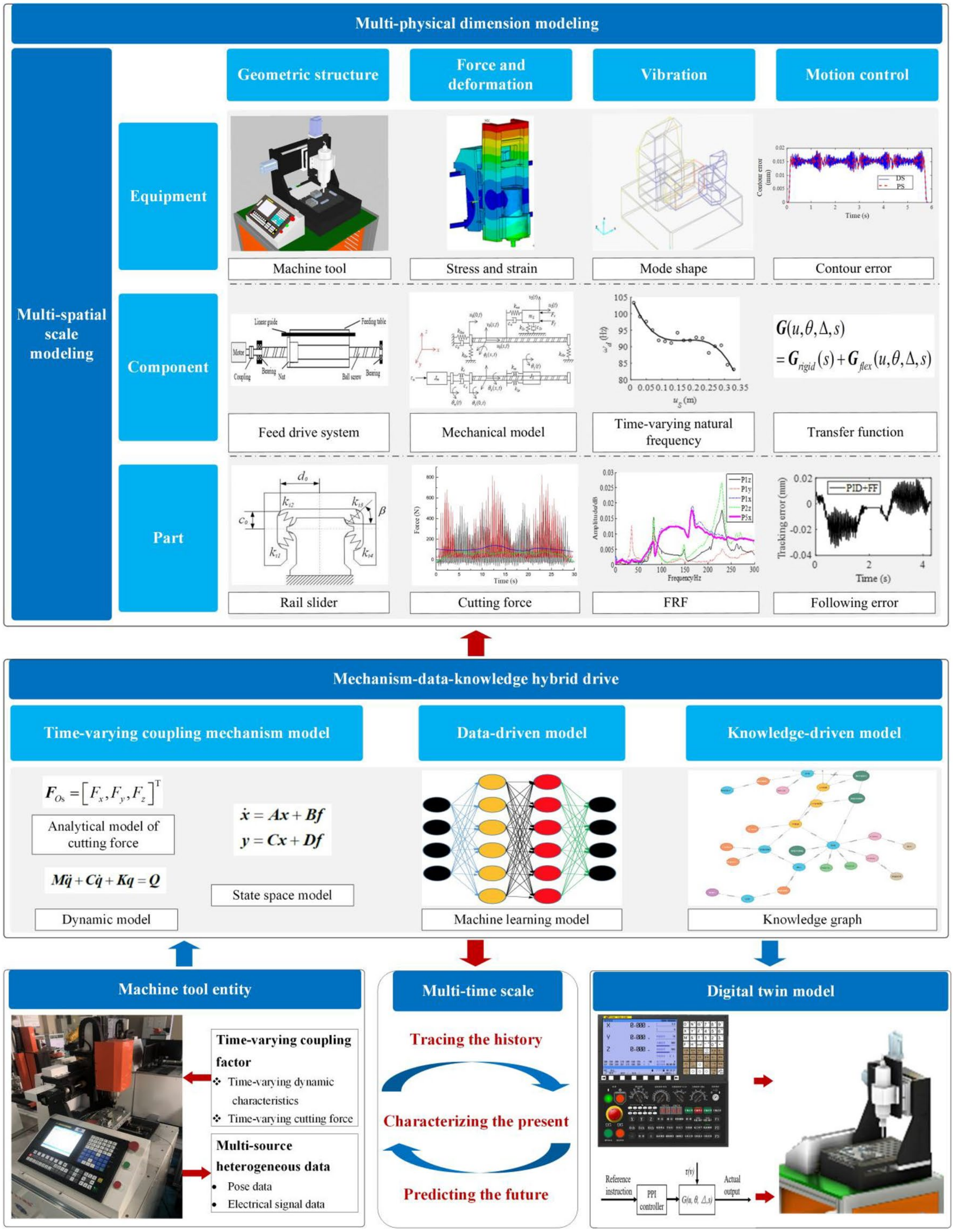

Figure 9 Framework of digital twin modeling and virtual-real synchronization technology of mechanism-data-knowledge hybrid-driven multiscale and multidimension

the force and deformation of the machine tool and its components. In the vibration dimension, the dynamic equation and state-space model of the machine tool and its components are established to characterize their modal shape, natural frequency, and frequency response function. In the dimension of motion control, the transfer function and servo control model of the machine tool and its components are established to characterize the following and contour errors of the machine tool. These multi-dimensional models are classified as mechanism models, capable of depicting the performance of machine tools. However, to improve the computational efficiency of these models, simplifications and assumptions are typically made in mechanism modeling. For instance, a machine tool part is typically simplified as having a few degrees of freedom in a dynamic model, and a complex mechanical system is simplified as a low-order system in the transfer function. This makes it difficult for the mechanism model to accurately represent machine tool performance. Furthermore, the real-time synchronous evolution of the model and entity cannot be guaranteed.

The perception data of the machine tool entity are combined with its mechanism to drive the digital twin model to characterize the machine tool performance accurately and dynamically. They also drive the synchronous evolution of the digital twin model with the machine tool entity and improve real-time synchronous evolution. In the dimensions of the geometric structure, parametric geometry models of the machine tool and its components are established using perceived data to dynamically represent the topological relationship between the machine tool and its components. In addition, the pose data drive the model to move synchronously with the machine tool entity, and the real-time reaches the millisecond level. In the dimensions of force and deformation, combined with machine learning algorithms and mechanism models, a surrogate model is trained using force and deformation data. Physics-informed machine learning represents a potential method [79, 80]. The surrogate model can dynamically characterize the force and deformation of the machine tool and its components. It can also improve the real-time synchronous evolution between the model and machine tool entity. In the vibration dimension, the dynamic mapping relationships of stiffness, natural frequency, and mode shape with the machine tool pose and load were established using the same method [79, 80]. The time-varying dynamic characteristics of the machine tool and its components were dynamically characterized, and the real-time evolution of the model with the machine tool entity was ensured. In the motion control dimension, the surrogate model, dynamic mapping relationship, and control strategy are combined to establish the control model of the machine tool. The contour and following errors are dynamically characterized, and the synchronous evolution of the model with the machine tool entity is driven by the perceived data.

A rule for the evolution of the digital twin model with a machine tool entity is described based on knowledge. The hidden knowledge in the mechanism and data is discovered using data mining, and knowledge accumulation is completed. Through knowledge modeling, knowledge graphs, knowledge fusion, and other technologies, single-point fragmented knowledge is processed to form a multipoint cross-fusion knowledge network that represents the evolution rule of the digital twin model. Powered by real-time data, the digital twin model achieves synchronous symbiosis with the physical machine tool. In addition, a knowledge network is employed to characterize the intrinsic associations between models with multiple physical dimensions, thereby facilitating the comprehensive integration of the digital twin model.

With the mechanism-data-knowledge hybrid drive, the machine tool and its operation process are accurately and dynamically characterized by the digital twin model, and the synchronous symbiosis of the digital twin model with a machine tool entity is realized. Additionally, the digital twin model simulates and traces the historical state and performance of a machine tool entity to determine the cause of failure. It also predicts the machine tool performance and provides a reference for controlling the machine tool operating parameters. The constructed digital twin model can accurately characterize a machine tool and its operation process at various timescales, which is an important basis for machine tool intelligence.

3.2.3 Dynamic Optimization and Collaborative Control Technology of Multilevel Parameters

The multilevel parameters of the machine tool include parameters in the process, interpolation, and servo layers. The process layer parameters included the spindle speed, cutting depth, and feed speed. The parameters in the interpolation layer are the feed rate, acceleration, and jerk of the machining path. The parameters in the servo layer include the proportional gain of the position loop (P_p) and the proportional gain (P_v) and integral gain (I_v) of the velocity loop. These parameters were coupled with each other. For instance, feed-rate scheduling is typically constrained by the closed-loop performance of a servo control loop. Servo control and parameter tuning primarily consider the influence of the parameters in the process and interpolation layers. In addition, these parameters affect the machine tool performance, and there is a nonlinear dynamic relationship between them and the performance parameters of the machine tool. Existing methods focus on the control of single-level parameters, the controlled parameters are relatively conservative, and machine tool efficiency has not yet been fully achieved. A dynamic optimization and collaborative control technology for multilevel parameters is proposed to provide technological support for implementing the DTMT.

The framework of the dynamic optimization and collaborative control technology for multilevel parameters is shown in Figure 10. Using the measured and simulated data, a dynamic mapping model of multilevel and performance parameters is established. On this basis, the dynamic prediction of machine tool performance is completed using the measured data of multilevel parameters. Based on the dynamic prediction results, a dynamic multi-objective optimization function-oriented toward machine tool performance is established. The Pareto solution, which refers to the optimal parameter sets in the process, interpolation, and servo layers, is calculated. These optimal parameter sets change dynamically. This change period is consistent with that

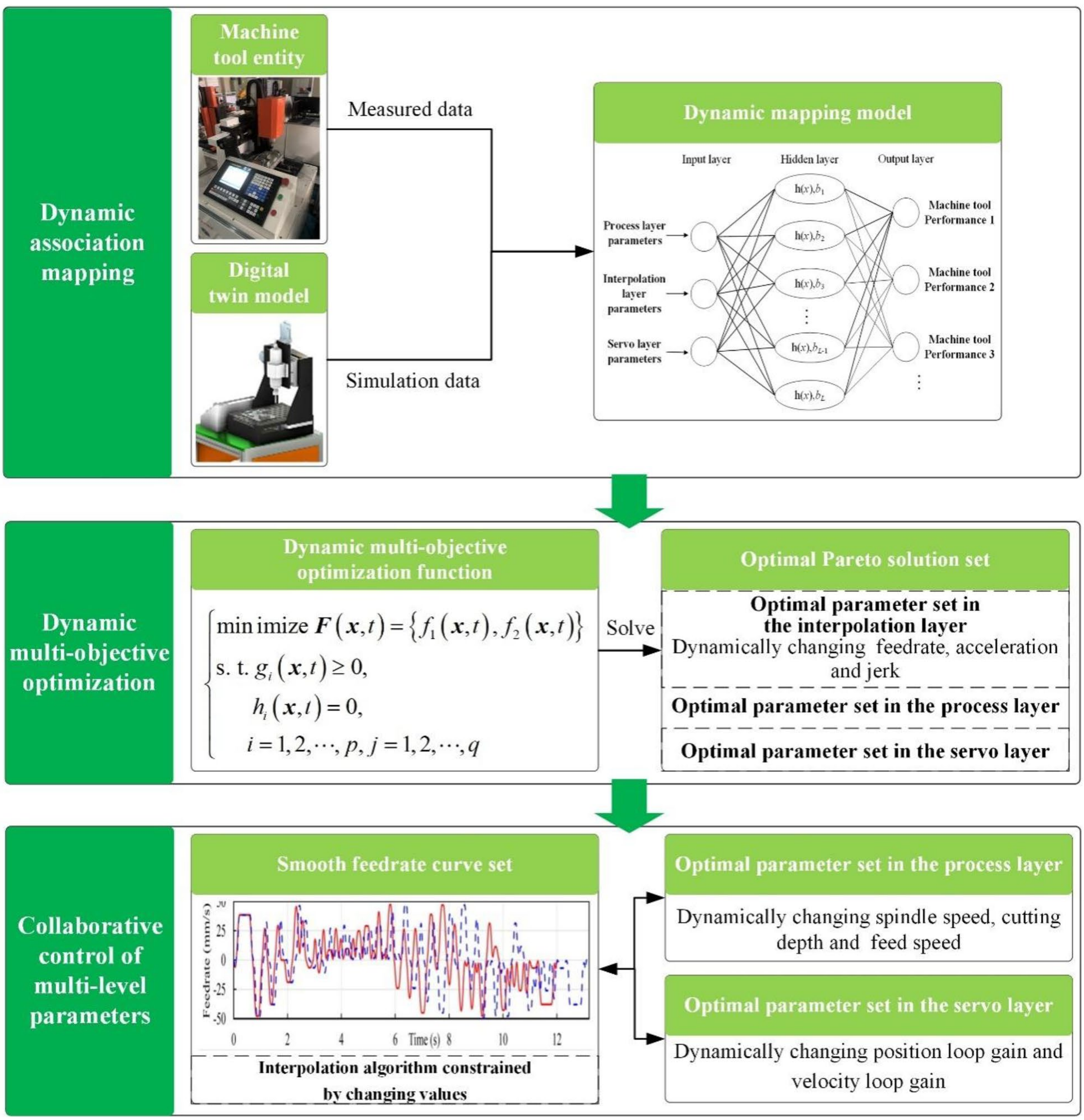

Figure 10 Framework of dynamic optimization and collaborative control technology of multilevel parameters

of prediction. Using the optimal parameter set from the interpolation layer as a constraint, the machining trajectory undergoes smoothing and feed rate scheduling, resulting in a set of smooth feed rate curves that dynamically adapt. The smooth feed rate curve set, coordinated with the dynamically changing optimal parameter sets in the process and servo layers, is employed as the control input to realize real-time control of the machine tool performance.

In the dynamic mapping model, data related to multilevel parameters, contour errors, cutting forces, temperatures, and other factors are typically collected. Data on deformation and dynamic characteristics can be simulated when necessary.

The dynamic multi-objective optimization function-oriented to machine tool performance is expressed as follows:

$$\begin{cases} \text{minimize } \boldsymbol{F}(\boldsymbol{x}, t) = \left\{ f_1(\boldsymbol{x}, t), f_2(\boldsymbol{x}, t), ..., f_n(\boldsymbol{x}, t) \right\}, \\ \text{s.t.}, g_i(\boldsymbol{x}, t) \geq 0, \\ \quad h_i(\boldsymbol{x}, t) = 0, \\ \quad i = 1, 2, ..., p, \ j = 1, 2, ..., q, \end{cases} \tag{1}$$

where $\boldsymbol{F}(\boldsymbol{x}, t)$ represents the objective vector that refers to the machine tool performance, such as the contour error and processing time. $\boldsymbol{x}$ represents the decision vector, which refers to the multilevel parameters. $\boldsymbol{g}(\boldsymbol{x}, t)$ and $\boldsymbol{h}(\boldsymbol{x}, t)$ represent the inequality and equality constraints, respectively, which refer to the constraints of the time-varying coupling factors such as the constraints of the time-varying dynamic parameters and cutting forces. t represents the time variable. The decision vector, objective vector, and constraints change dynamically over time. t is used to quantify the change frequency. The function in Eq. (1) is solved using dynamic multi-objective optimization algorithms, such as the forward forecasting strategy-based regularity-model-based multi-objective estimation of distribution algorithm (RM-MEDA) and steady-state and generational evolutionary algorithm (SGEA). The obtained Pareto solution dynamically changes, which includes dynamically changing the parameters in the process, interpolation, and servo layers.

Taking the feed rate, acceleration, and jerk of the machining trajectory in each change period as constraints, the trajectory curve for each change period is segmented, and the constraints of the segmented curves and scheduling parameters are obtained. The conventional method is adopted to smooth the curve corner and schedule the feed rate curve to obtain a smooth feed rate curve for each change period, which comprises the smooth feed rate curve set. The dynamically changing spindle speed, cutting depth, and feed speed; dynamically changing smooth feed rate curve; and dynamically changing P_{p}, P_{v}, and I_{v} are matched and coordinated in each change period. These collaboratively controlled parameters are used as the control inputs to realize real-time control of the machine tool performance.

In summary, during the DTMT operation, the machine tool performance is continuously predicted in real-time. Dynamic multi-objective optimization of the multilevel parameters is performed according to the prediction results, and the optimal multilevel parameter sets for each change period are obtained. Real-time control of machine tool performance is achieved by matching and coordinating the dynamically changing parameter sets of the process, interpolation, and servo layers. The above process is dynamic and is accompanied by an entire machine-tool operation process. This is key to implementing machine tool intelligence.

4 Development Trend of Digital Twin Machine Tool

With the improvement of computing power of computer software and hardware, the enrichment of intelligent algorithm, and the advances in industrialized integration of new-generation information technology, DTMT is developing toward full life cycle, cloud-fog-edge collaboration, and deep integration with new-generation information technology.

4.1 Full Life Cycle

As machine tool intelligence evolves, the DTMT should encompass the entire life cycle of machine tools, covering design, manufacturing, and service phases. In the design stage, the digital twin model is established based on machine tool design information, operating data of similar machine tools, and experience in machine tool manufacturing and service. Normally, design information includes a three-dimensional model, material properties, and control algorithm, which involves precision, failure, and reliability, and experience knowledge refers to the manufacturing process, maintenance information, and customer suggestions [38, 77, 133]. With the digital twin model and software platform, the design flaw was identified through high-confidence simulation and optimization and improvement were suggested [134]. When the design requirements change, the machine tool is quickly reconfigured and designed to respond. In the manufacturing stage, the dynamic update of the digital twin model is driven by the data and knowledge of machining and assembly, whose process is monitored in real-time. Based on the simulation of the digital twin model, the quality and performance problems of processing and assembly were identified, and the processing and assembly processes were optimized to achieve high-precision and high-efficiency manufacturing. In the service stage, the proposed architecture of the DTMT completes the smooth and reliable operation of the machine tool.

In the complete life cycle of the DTMT, various stages interact. The design result is an important basis for the manufacturing process, manufacturing quality provides a basic guarantee for service performance, and the knowledge of manufacturing and service is a reference for design optimization and improvement. The design, manufacturing, and service of the DTMT comprise a closed loop of iterative optimization and cyclic progression.

4.2 Cloud-Fog-Edge Collaboration

The large-scale and real-time transmission and management of data, integration and real-time synchronization of digital twin models, and real-time calculation of optimization and control algorithms have become key challenges for DTMT implementation. The cloud-fog-edge collaboration is being introduced into the DTMT to give full play to the advantages of cloud services, fog computing, and end-to-end transmission, which facilitates the successful implementation of the DTMT. In the edge layer, multisource heterogeneous data are perceived in real-time through the NC system, sensors, and other data-acquisition devices. Using Modbus, EtherCAT, and other protocols, the perceived data are transmitted to the fog layer for the collection and low-latency transmission of machine tool data. A digital twin model is established at the fog layer based on the mechanism-data-knowledge hybrid-driven method. Supercomputing power is employed to complete the efficient calculation of the intelligent algorithm, real-time simulation of the digital twin model, and real-time control of the machine tool entity. In the cloud layer, the simulated and measured data are received from the fog layer through protocols such as OPC-UA and TCP/IP. Using the integration and fusion capabilities of the cloud, data are processed using knowledge accumulation, knowledge fusion, and knowledge graphs. Customized services are provided for various requirements such as data visualization, process optimization, and health monitoring.

4.3 Deep Integration with New-generation Information Technologies Such as 5G and Augmented Reality/Mixed Reality

In the DTMT, the transmission of multisource heterogeneous data runs through the machine tool entity, digital twin model, and decision and control. Data transmission among the design, manufacturing, and service stages and the cloud, fog, and edge layers is the basic guarantee for DTMT implementation. The transmission of vast, varied data types using different methods poses significant challenges to maintaining data integrity, real-time performance, and efficiency, often surpassing the capabilities of current techniques. The 5G technology has high bandwidth and low latency. Therefore, the deep integration of 5G technology with all aspects of the DTMT can greatly improve the efficiency of data transmission, reduce delay, and ensure integrity. This guarantees the reliable operation of the DTMT.

The most notable features of the DTMT are virtual-real integration and synchronous symbiosis. Augmented reality/mixed reality (AR/MR) technology integrates virtual and real spaces into a seamless virtual-real world by introducing a virtual scene into a real environment, in which the physical entity and digital model coexist and interact in real-time. AR/MR technology coincides with the DTMT characteristics. The deep integration of AR/MR technology and virtual-real fusion algorithms is a major challenge for future research. The deep integration of AR/MR technology with digital twin modeling and synchronization methods will enhance the realism of human-machine interaction and is also a major challenge. AR/MR technology is set to elevate DTMT development, enhancing the integration of virtual and real environments to new heights.

5 Conclusions

Digital twin technology is foundational for the development of machine tool intelligence. However, there is a lack of clear and systematic analyses of digital twin-based machine tool intelligence. Therefore, according to an analysis of the correlation between machine tool intelligence and digital twin, digital modeling has been identified as a key enabling technology for machine tool intelligence. A digital twin modeling-enabled machine tool intelligence survey was conducted. The main conclusions are as follows.

(1) The survey was conducted from two perspectives: data-based and mechanism-data dual-driven modeling. Based on this, three bottleneck problems were presented, which include virtual-real fusion of multisource heterogeneous data, digital twin modeling and synchronous mapping of machine tools and their operation processes, and real-time and collaborative control of machine tool operating parameters. This provides a theoretical guide for research on machine tool intelligence.

(2) Aiming at the three bottleneck problems, a DTMT architecture was proposed, and its three key technologies were elaborated, which include data perception and fusion technology, digital twin modeling and virtual-real synchronization technology with a mechanism-data-knowledge hybrid drive,

and dynamic optimization and collaborative control technology of multilevel parameters. This provides technological support for implementing machine tool intelligence.

(3) The full life cycle, cloud-fog-edge collaboration, and deep integration with new-generation information technology are considered three important directions for the future development of the DTMT, which provides a reference for future research on machine tool intelligence.

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Authors' Contributions
LZ was in charge of the material preparation, data collection, and analyses, and wrote the manuscript. All authors read and approved the final manuscript.

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Data availability
The data used to support the fndings of this study are included within the article.

Declarations

Competing Interests
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