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Construction Method of Digital Twin System for Thin-Walled Workpiece Machining Error Control Based on Analysis of Machine Tool Dynamic Characteristics

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Abstract: In the intelligent optimization process of aerospace thin-walled parts, there are issues such as solidification of core knowledge base, high system coupling degree, and real-time evaluation and optimization feedback required for the knowledge base. These problems make it difficult to expand the functions of the digital twin system and meet the growing processing needs, ultimately hindering the application of digital twin technology. To address these issues, a digital twin system for controlling processing errors in thin-walled parts was built using a microservices architecture. In addition, a method for building a digital twin system at the processing unit level with the best coupling degree was proposed, mainly targeting the dynamic characteristics analysis knowledge base of thin-walled parts. Furthermore, to meet the requirements for backward compatibility of the processing unit level digital twin system, a comprehensive solution including the construction, operation, evaluation, optimization, and visualization of a knowledge base for the dynamic characteristics of the processing unit was proposed, providing guidance for the digital transformation and upgrading of CNC machine tools and the optimization of processing technology based on digital twin technology.

Keywords: CNC machine tool; digital twin; micro service; dynamic characteristics; module coupling

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1. Introduction

In aerospace industry, weak rigidity thin-walled components are widely used. There are several definitions to characterize thin-wall components, and typically "thin-wall" is defined by a large ratio of wall length to wall thickens [1]. The most common thin-wall components in aviation, aerospace, and the energy industry include aircraft structural parts, impellers, and turbine blades [2].

These components are characterized by complex structures, thin walls, weak rigidity, and high requirements for surface precision. During the milling process of weakly rigid thin-walled components, there exist extremely complex state changes among the machine tool, workpiece, and cutting tool, which also mutually influence each other. It is worth noting that changes in the relative positions of the spindle and the rotary table can cause changes in the dynamic characteristics of the machine tool. Furthermore, the comprehensive dynamic performance of the cutting system will also vary. All of these factors have a significant impact on the quality of the cutting process.

Wu et al. established a machine tool dynamic model by dividing the mechanical system into three types of elements: rigid body, flexible body, and connection surface. The model utilizes the Extended Transfer Matrix Method, which is suitable for dynamic analysis of machine tools. By solving the mathematical matrices of the three types of elements and performing calculations on high-dimensional matrices, the dynamic characteristics of the entire machine tool can be easily obtained [3]. Liu applied the theory of multibody system kinematics to the model building process of multi-axis CNC machine tools has achieved significant results [4]. Zhao et al. proposed a dynamic analytical modeling method for the spindle rotor system, which elaborates in detail the contact characteristics between the tool-holder, tool-holder-sleeve, and spindle-tool-holder interface [5]. Li et al. started with the key dynamic performance of ultra-precision machine tools, and analyzed the mathematical relationship between the dynamic performance of the machine tool and its position and orientation. They employed spatial statistical methods to establish a Kriging method model based on the machine tool dynamic characteristic variation function, which can predict the change of machine tool dynamic performance and demonstrate the change pattern of dynamic characteristics in the machining space of the machine tool [6]. Yang et al. collected dynamic characteristic data of a machine tool from the same location. However, the study showed that data from a single location cannot well reflect the dynamic characteristics of the entire machining space, and an analysis method for the dynamic characteristics of machine tools in the machining space be proposed [7]. Zaghbani et al. proposed a modal analysis method that can predict the dynamic modal parameters of the machine tool during the machining process [8]. Silva et al. discussed the integrated design issues related to the dynamic changes of mechatronic systems [9]. Y. Altintas et al. discussed the relevant technologies involved in virtual machining and found that one of the sources of machining instability is the change in the vibration modes of the system, which is caused by the cutting force during the cutting process [10,11]. Petr Kolar et al. analyzed the relationship between machine tool dynamic characteristics and cutting tool endpoint dynamic characteristics through physical experiments and simulation models [12].

Currently, most of the research on performance calibration of machine tool components focuses on the stationary state of each component. However, the moving components of the machine tool will undergo changes during the machining process, involving relative spatial positions, angles, coupled force vectors, and so on. At the same time, the dynamic characteristics of the main spindle pose points in the working space of the machine tool will also vary at different times. Most current research lacks this kind of investigation, which delves deeply into the impact of time-varying dynamic characteristics on machining errors and control strategies.

It is critical to note that the effects mentioned above are highly relevant to the milling process of weakly rigid thin-walled components. As such, understanding and controlling these effects is imperative to ensure the high-quality manufacturing of such components. By elucidating the mechanisms behind these effects and devising strategies to mitigate their negative impact, significant advancements can be made towards the development of more efficient and effective milling processes for weakly rigid thin-walled components.

Budak proposed a novel design method for variable pitch cutters, which is used to suppress chatter during the flank milling of gas turbine blades [13]. Smith performed a time-domain simulation of the milling process and used the peak-to-peak graphs to evaluate the cutting force and variation information [14]. Wu et al. proposed a method for optimizing the distribution of machining allowances during the overall milling of turbine blades. This method was applied during the machining process. Their simulation results showed that this method improved the stiffness of the system by a factor of 2 and increased the stability limit of chatter by a factor of 3 [15]. Lu studied the effect of the tool's movement along the length of the workpiece on the stability of chatter. During high-speed cutting, the difference between the predicted tool position and experimental results was within 9% [16]. Ferry proposed a method that includes a semi-discrete and solid modeling approach to simulate the five-axis flank milling of engine blades in a virtual environment. They also developed a cutting force prediction model for five-axis flank milling that considers multiple factors, including five-axis motion, sawtooth shape, variable helix, taper, helical ball end milling cutters, and irregular tool-workpiece engagement. Finally, they developed two offline optimization methods for optimizing the linear and angular feed rates of the five-axis flank milling of blades [17]. Wang using CAM software to simulate the milling process, the cutting path for structural modification is divided into multiple cutting steps to obtain the corrected FRF. Finally, an extended numerical integration method was used to predict the stability of multi-axis milling, and the effectiveness of the method was verified using aircraft engine blades as an example [18]. Qin proposed a feed rate variation strategy for ball-end milling of thin-walled workpieces with semi-conical shape. The strategy takes into account the shape and boundary conditions of the workpiece as well as the contour tool path of the milling process to obtain predictions of cutting forces, dynamic performance, and stability. Experimental results showed that the strategy saved about 25% of time while achieving almost the same machining quality [19]. Olvera considered the helical angle, runout and cutting speed effects to calculate the stability diagram. The validity of the method is verified by machining experiments on aluminium alloy thin-walled parts [20]. Wang proposed a model of instantaneous and undistorted chip thickness for runout error and dynamic deformation during micro-milling. The experimental results show that the micro-milling force model has better prediction accuracy, and the difference between the predicted resultant force and the experimental results is less than 11% [21].

The above-mentioned method can obtain more precise and accurate machining paths and cutting parameters, which has made an important contribution to preventing chatter and improving machining limits. However, the optimization of tool paths depends on commercial CAM software or secondary development based on existing CAM software, which limits its functionality. On the other hand, due to the consideration of many related factors, more computation time is required, and the layout of distributed computing is not taken into account to improve computational efficiency.

Traditional research methods cannot be directly integrated with the data flow of the machine tool production process. This means that these methods cannot effectively evaluate the production process by inputting the state of the machine tool at different working spaces and times, while it is difficult to meet the requirement of real-time quantitative evaluation.

The research on real-time quantitative evaluation methods for processing systems is the foundation for achieving "full perception" of intelligent cutting processes and is also a major source of data for processing information fusion. It is a module that integrates multidisciplinary knowledge to make cross-disciplinary judgments on processing technology. Currently, research on process evaluation is mostly focused on single physical models or single disciplines. There are several problems with single-method-based research: first, the algorithm's applicability is poor due to inadequate matching between the model and the scene perception, which affects the accuracy of the results and the feasibility of the optimized processing strategies. Second, the evaluation methods are not verified for a unified processing scenario, making it difficult to fully demonstrate the applicability of the evaluation methods. Third, there is rarely a comprehensive observation and explanation of the problem from multiple perspectives, the perspective is too one-sided, the problem-solving ideas are relatively single, and it is impossible to complement each other's strengths and weaknesses. Based on these factors, a digital twin system for CNC machine tools was built for the processing of thin-walled parts.

The concept of digital twin has been proposed as a way to reduce unpredictable and unwanted emergency situations in complex systems. Due to its advantages in reducing maintenance costs, improving productivity, and shortening production time, digital twin has been researched and applied in various fields [22–24]. Taking the research on digital twin of machining units as an example: Tong et al. established a digital twin model of intelligent machine tools, which improved the process of data analysis and optimization results, including machine tool dynamics, contour error estimation and compensation, and other aspects [25]. Luo conducted research on key technologies for predictive maintenance of CNC machine tools. This study, based on digital twin technology, includes digital twin architecture, model modeling methods, scenario perception methods, data fusion and predictive maintenance methods, and finally applied and validated [26]. Jiang studied the optimization of tool path in machining by constructing a digital twin of the machine tool, and designed and optimized the tool path of the CNC machine tool by monitoring the real-time operation status of the CNC machine tool in the digital space [27]. The characteristics of digital twin technology provide new impetus for the transformation and upgrading of manufacturing units. These characteristics include the fusion of virtual and real environments with real-time interaction, iterative operation and optimization, all-element, all-process, and all-business data-driven [28,29].

During the production process, new problems with different forms will arise, which requires the digital twin system to have good flexibility and robustness, enabling it to transition from the initial functionality at the design stage to newly added functionalities, thereby adapting to specific production needs.

At the same time, when designing the digital twin system, designers not only need to delve into the professional knowledge required for the system but also consider the system architecture from a holistic perspective, focusing on responding to future demand changes, thinking about potential problems, and preparing specific strategies on the design diagram. If we consider the factors of technology update and iteration, it is worth noting that the interdisciplinary coupling of the digital twin system largely increases the possibility of technological updates and iterations. Therefore, in the process of putting the system into production, as technology updates and physical machine tools add new sensors, new requirements are placed on quality and processes. The digital twin system in the digital space should also be able to keep up with these changes in a timely manner, provided that this was considered from the beginning of the system's creation.

However, the solidification of core knowledge base in the manufacturing unit, high system coupling, and issues such as knowledge base-assisted real-time processing evaluation and optimization feedback make it difficult to expand the functionality of the digital twin system. Therefore, it is necessary to adopt a design scheme that reduces the coupling degree between various modules of the twin system, enhances the embeddability of knowledge into the knowledge base, so as to reduce the development cost and lower the difficulty of subsequent functional updates and iterations.

By utilizing digital twin technology, a digital twin system for complex equipment objects can be built for specific production processes. By inputting the data flow loop into the machine tool dynamic characteristic knowledge base, using data cleaning analysis, feedback training, and ultimately improving the model accuracy, production problems can be solved and production quality can be improved. This not only requires the digital twin system to be reasonably segmented and accurately modeled for complex scenarios, but also to be compatible with various algorithm models, with good scalability and robustness.

2. A Digital Twin System Architecture for Evolvable Machine Tools

2.1. Basic Structure

During the design phase, a low-coupling architecture was adopted, and the CNC machine tool entity was divided into many functional modules. The division of these modules also took into account the actual problems to be solved and the overall requirements of the digital twin system, considering mapping content, information flow, core elements, and other aspects, as shown in Figure 1. While minimizing the coupling relationship between modules, the constructed digital twin system has the ability to expand its functions. This is to prepare for future physical space changes and twin system upgrades, thereby meeting future needs. The solution is based on the full lifecycle of the digital twin system, which greatly affects the use of the processing unit digital twin system and the development plan of functional modules, indicating that the project will go through a process of continuously adding and modifying functional modules. However, by reducing the coupling degree between functional modules and considering optimizing the difficulty of frequent addition and deletion through architectural design before building, the modules in this system can be called in other systems to improve computing power and increase system robustness.

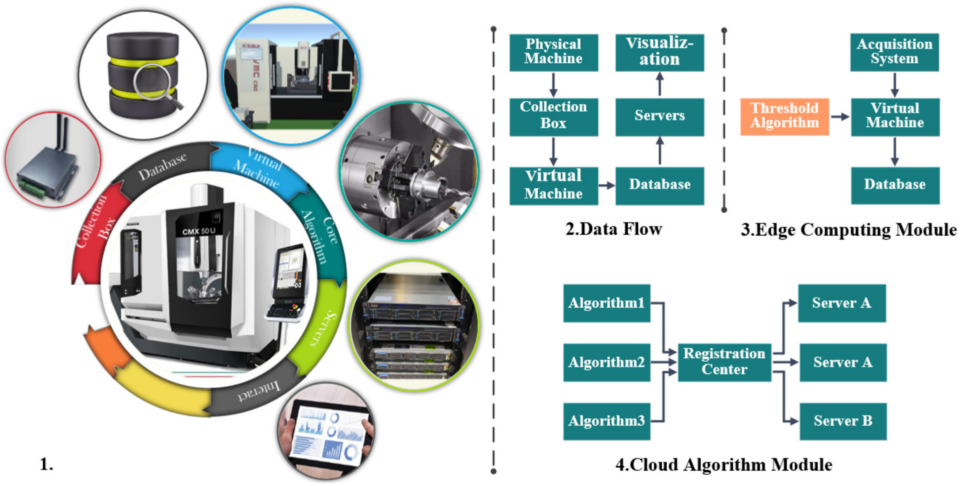

Figure 1. Digital twin system elements and information flow of processing units. Include: 1. The main components of the digital twin system; 2. Data Flow Support in Digital Twin Systems; 3. The embedding algorithms and data; 4. Algorithm scheduling for parallel architecture.

2.2. Architecture Design to Reduce Coupling

The architecture of the digital twin system for the machining unit involves the physical space of the CNC machine tool, the digital twin system, and the data transmission between the two. Software and hardware need to be comprehensively considered: not only should they be able to undertake complex tasks such as computation, big data processing, visualization display, and data transmission, but they should also integrate advantageous frameworks based on the existing framework, continuously upgrade and update, and realize the iteration of the digital twin system, thereby improving the twin model.

As shown in Figure 2, a processing unit-level digital twin system architecture based on microservice theory is proposed, considering the coupling characteristics of multiple knowledge bases, functional scalability, and robustness. Based on SpringBoot [30], the digital twin microservice system is built, and Docker container technology [31] is used to simplify the construction, deployment, and operation process of microservice applications in the processing unit twin system. To solve the problem of management complexity caused by the continuous increase of microservices and the growth of the twin system application functions, the Kubernetes [32] framework is used to achieve automatic deployment of system functions and automatic scheduling of resources. At the same time, the OpenFeign [30] framework is used to build a system task assignment mechanism to ensure load balancing of the twin system server.

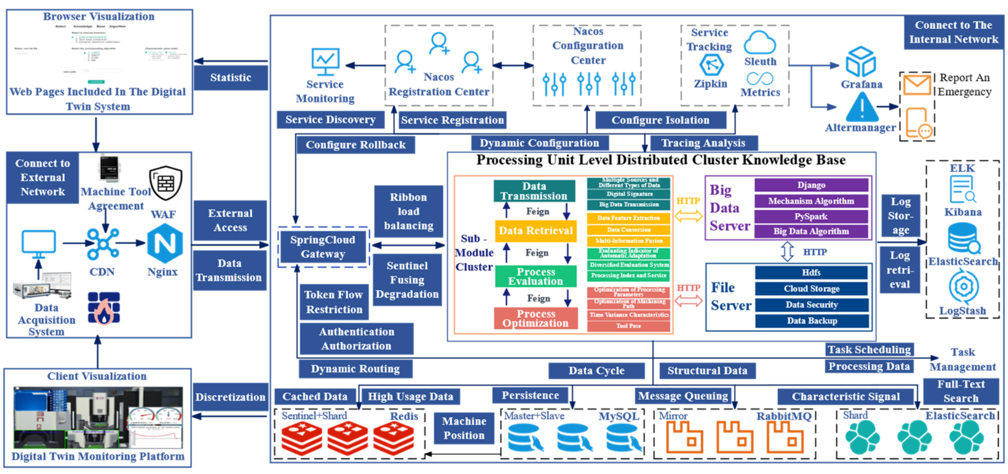

Figure 2. Microservice Architecture of Digital Twin System for Machining Units.

To achieve the real-time read-write tasks of high-frequency data such as the real-time position of the spindle, spindle speed, and machine tool rotary table angle information, Redis, MongoDB, and other cache frameworks are studied for their application in the processing unit digital twin system. According to the data type, the data analysis business process is divided, and the structured data of multiple sources of information monitored during the machining process (cutting force, cutting vibration, etc.) are stored persistently in the MySQL database. The visualization layer data such as tool wear is handled by the Hadoop framework for data read-write business. To complete the retrieval task of complex data, ElasticSearch [30] search engine is combined with the structured data of the machining process. To ensure message caching, persistence, improve fault tolerance and throughput of the digital twin system, Kafka [33] is used as a message broker in the server cluster. Nginx [30] is used to deploy the gateway and realize information interaction between modules in the digital twin system.

A rolling data-discretization model-driven method for inverse modeling of machining processes is proposed to enhance the matching between the model and the functionality of the digital twin system, achieving deep exploration and dimensionality analysis of the monitoring data of machining processes. To improve development speed, ensure application security, and maintain compatibility with databases, URL routing, middleware, view layer, and model layer, a digital twin system algorithm server is built using the Django [30] framework. Distributed and efficient computing is realized by introducing micro-batch and streaming frameworks such as Spark Streaming or Flink [30]. To enhance the speed and accuracy of the mechanistic model, the collected data is connected to the server-side data rolling model through the http/https protocol to improve the data interaction efficiency between the main server-side and the visualization side.

3. Functional Module Development

This section introduces the various modules of the digital twin system for machining units. The digital twin system for machining units, built in a microservices architecture, includes the following modules: data acquisition, storage, computation, transmission, invocation, visualization, and other related issues.

3.1. Data Acquisition and Transmission Module of Digital Twin System

The data acquisition module is a module that receives data from data acquisition devices or obtains machine tool operating signals through CNC protocols, and requires end-to-end data read/write capabilities as well as data storage design. Data acquisition devices include various types of sensors (such as cutting force, power, acceleration, acoustic emission, temperature, etc.), cameras, RFID tags and readers, signal processing equipment, etc. The machine tool protocol is based on the CNC system of the machine tool and uses protocols such as OPC-UA, MT Connect to obtain information such as the feed axis coordinates, speed, load, and alarm signals of the machine tool. Currently, industrial data acquisition devices are more of a combination of the two. Since the collected data may come from different machining units with different collection frequencies and expression attributes, higher requirements are placed on the design of the database and the transmission of data. Moreover, the increasing input devices such as sensors require greater scalability of the data acquisition module and database. The remote multi-source nature of the equipment poses a challenge to the high concurrency of the machining unit twin system.

To address the above issues, when designing the data acquisition module, frequent read-write and high real-time requirements for data such as the feed axis and feed axis load of the processing unit are separated and stored in different tables and databases. Redis, Memcached, and other caching architectures are introduced to alleviate the pressure of database read-write operations and optimize the structure and indexes of the database. The configuration is managed uniformly in Nacos to meet the needs of expansion and improve the robustness of the system. The management of heterogeneous data from multiple sources, as well as the threshold processing of data, are included in the preprocessing module to reduce the difficulty of data storage and processing. At the same time, the low coupling design makes it easier to adapt to future technology updates and the increasing demand for data acquisition. Based on the data obtained by this module, intelligent calculations and mining can be performed in other modules, and machine tool state data can be provided for application scenario analysis.

Additionally, as shown in the Figure 3, the data storage of the digital twin system is managed by the data storage server. The collected sensor data, workpieces, tools, machine tools, and other information are saved in the data storage server and corresponding databases and data tables are established in the server. Considering the data types, structured data such as CSV and TXT are stored using MySQL, while unstructured data such as MP4 and PNG are stored using NoSQL to achieve reasonable data storage. Furthermore, the data storage server is responsible for data caching function and improves data flow read and write efficiency by accessing the data caching framework. Meanwhile, by establishing the data storage server, data can be transmitted within the LAN. Combined with network servers and microservice frameworks, parallel scheduling can be achieved between the intranet and internet, laying a foundation for improving computing efficiency.

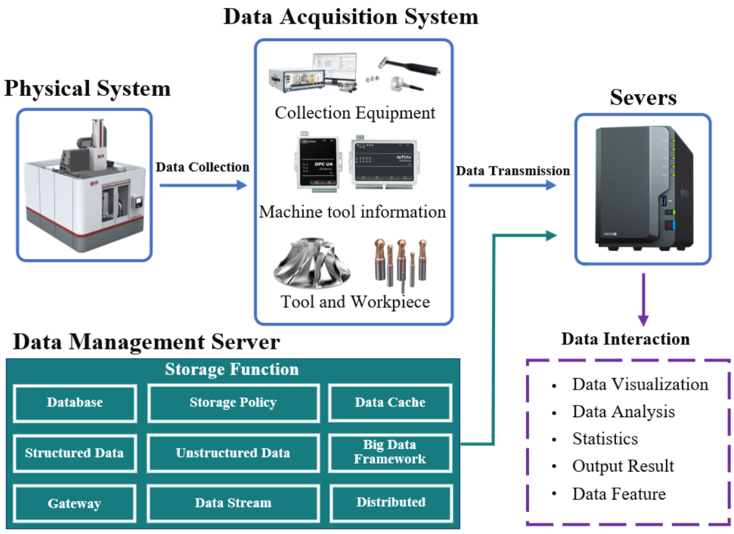

Figure 3. Digital Twin System Information Acquisition Module.

In the process of data transmission and utilization, corresponding domain knowledge such as fitting, filtering, and threshold processing units can be added to this module to alleviate the pressure of data transmission, and achieve pre-processing, feature extraction, and feature selection of machining data. This lays the foundation for the visualization demonstration of the CNC machine tool digital twin model, the evaluation of machining process strategies, and the optimization of machining processes.

3.2. Digital Twin System Algorithm Module

The algorithm module is a module that further utilizes the collected machine tool sensor data and simulation result data. By including various types of algorithms to extract data features, reduce noise in data, or analyze mechanisms, it explores the physical meaning behind the data and finds the cause of problems. For a digital twin system, the algorithm module is more like the brain of the digital twin system, which can efficiently process large amounts of data, clean and analyze data effectively, thereby improving the accuracy of the model, and the final results are displayed by the visualization module of the digital twin system. This makes the module require the following points: (1) can accommodate various different algorithms, and the operation of the algorithms does not affect each other. (2) The module can transfer information to other modules. (3) The algorithm can continuously improve the accuracy according to data growth. (4) Able to adapt to distributed computing requirements and improve computing efficiency.

Considering the above requirements, Python language has advantages in big data algorithms. The algorithm server of the machining unit digital twin system was built through the Django framework, and the embedded Python language algorithm in the server can complete the calling of various big data algorithms, and they are relatively independent of each other. Data transmission between modules is carried out in JSON format through HTTP protocol to improve the information flow between modules. Through the formed closed-loop digital twin system, data is deeply mined, and model accuracy is improved through data rolling, thereby continuously improving the advantages of the machining unit digital twin system.

In this digital twin system, with the help of microservice architecture, multiple types of Kriging algorithms and path optimization algorithms are embedded in the built algorithm server to calculate experimental and simulation data, and obtain the machine tool dynamic characteristics in the machining unit workspace. The results can be called by the machining process optimization module of the digital twin system through load allocation.

3.3. Processing Unit Processing Process Evaluation Module

The emergence of digital twins provides ideas for solving the above problems. By constructing a processing technology evaluation module in the twin system, this module allows for exploration of problems from multiple perspectives based on the evaluation rules provided in the knowledge base. It can also comprehensively evaluate multiple evaluation schemes for the same processing area, provide evaluation results, guide the development of globally optimal processing technology optimization schemes, and achieve process optimization for specific processing scenarios. Taking impeller machining as an example, the same machining path evaluation for impellers can be obtained through different evaluation methods from the dynamic characteristics knowledge base in the previous step. At the same time, it is possible to choose whether to use a single optimal evaluation rule to evaluate the results or to use a combination of multiple evaluation rules to evaluate different areas [as shown in Figure 4]. This approach can not only bind application scenarios with processing strategies but also combine evaluation methods with evaluation areas, providing the possibility for verifying multiple processing strategies in the same physical model. Through multidisciplinary cross-evaluation, the evaluation perspective can be more systematic and comprehensive.

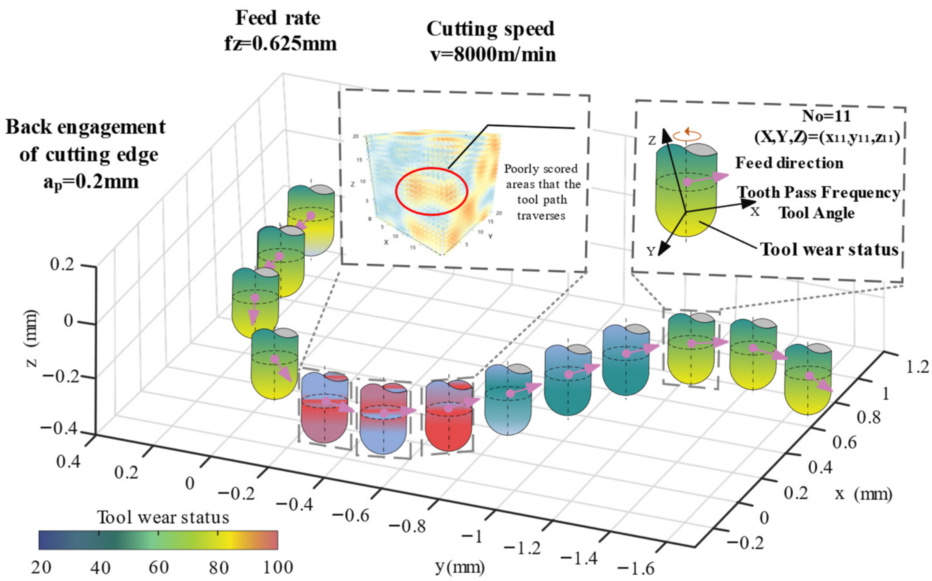

Figure 4. Evaluation of spatiotemporal dynamic characteristics spectrum of processing system.

In addition, this module needs to provide feedback to the corresponding evaluation indicators in the knowledge base module based on the processing results. The purpose of this is to indicate the direction of improvement and upgrade for the knowledge base, and the predictive accuracy, computational efficiency, and the ease of conversion into dynamic evaluation indicators all affect the effectiveness of this module.

3.4. Processing Unit Processing Process Optimization Module

The module of process optimization for machining units is responsible for optimizing the machining process by adjusting process parameters, tool paths, tool positions and orientations, and selecting optimal tools based on the results of the evaluation module. It builds on the evaluation results from the previous module and aims to address any regions that do not meet the required machining specifications. By calling upon the results from the evaluation module, it proposes improvement strategies and solutions for specific machining system parameters at non-compliant tool positions, and stores the optimized information in the database container for future reference. In addition, the optimization information is converted into machine-executable code and used to control the machining process by adjusting the spindle speed in a closed loop, completing the operation in the virtual space.

When selecting machining parameters for impeller blades, it is necessary to ensure the surface quality of the machined surface and maximize machining efficiency. The machining error e and the machining efficiency MRR are selected as the optimization objectives, and the optimization parameters are the rotational speed v and the spindle feed rate [as show in Figure 5]. Before optimizing the machining parameters, the functional relationship between the optimization parameters and the optimization objectives and the evaluation function for evaluating the optimization effect should be clarified. Due to the existence of the digital twin model, after inputting the specific machining object and process into the digital twin evolution knowledge base, the machining error e and the chatter frequency of the current process can be obtained based on the generated dynamic characteristic field and machining code, by inputting parameters such as the rotational speed and the spindle feed rate.

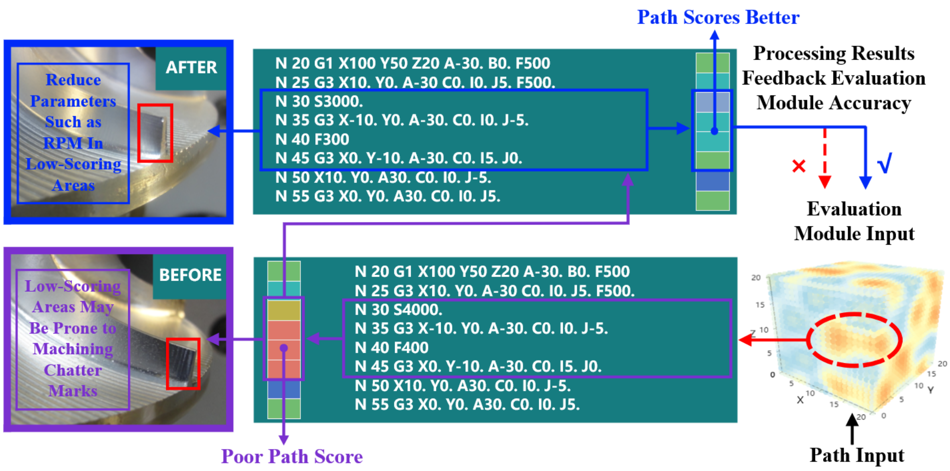

Figure 5. Optimization and feedback strategy of processing unit processing technology.

3.5. Visualization Module

The visualization module is a tool for presenting data and the processing process in a clear and intuitive way. It can exist in the form of a browser, client, or mini-program. Since most of the computing is done on the server side, the role of the visualization module is mainly to interact with the user, and the priority of its content needs to be distinguished. The HTTP protocol is used as the communication protocol between the visualization module and the server.

4. Experiment and Analysis

4.1. Experiment and Simulation

The research machine tool is a five-axis machine tool, and the travel ranges of the five axes XYZAC are as follows: 1080 mm in the x direction, 710 mm in the y direction, 710 mm in the z direction, 120° in the A axis (spindle swing), and 360° in the C axis (worktable rotation). The position of the machining space is sampled, and the changes of the five axes are taken as experimental variables. The experimental equipment used is the Donghua Testing and Detection Platform as shown in Table 1, which tests the frequency response of the acceleration of a point on the spindle end of the machine tool at each sampled position through force hammer excitation. The experimental site is shown in Figure 6. Based on the travel ranges of XYZAC and the number of experiments, the rationality of uniformly distributing the sampling points is analyzed, and a position table is established as shown in Table 2.

Table 1. Main equipment for modal experiments.

No	Device Name	Equipment Model	Purpose
1	impact hammer	Handheld impact hammer	Input excitation
2	Acceleration sensor	PCB	Picking up acceleration signal
3	Data collection and analysis system	DH5922	Collect and store signals

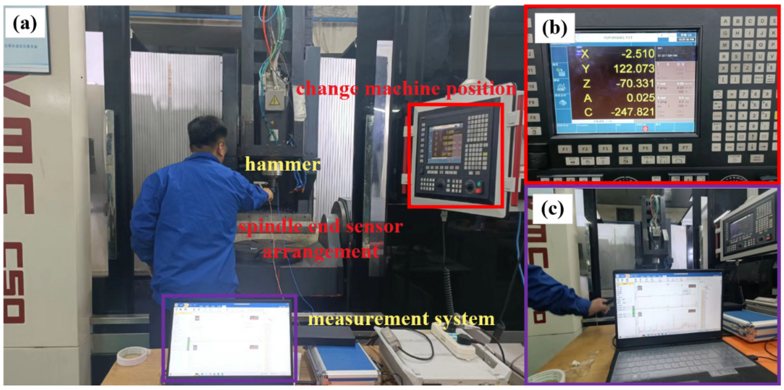

Figure 6. Modal experiment: (**a**) experimental test scenario (**b**) machine tool spindle position (**c**) modal test system.

Table 2. Processing positions of test samples.

No	X/mm	Y/mm	Z/mm	A/°	C/°	No	X/mm	Y/mm	Z/mm	A/°	C/°
1	−125	125	0	−25	90	5	125	125	0	0	180
2	−125	375	−100	0	180	6	125	375	−100	50	270
3	125	125	−200	25	270	7	−125	125	−200	−25	90
4	125	375	−300	50	360	8	−125	375	−300	25	360

Figure 7 shows the modal simulation of the machine tool in the same attitude. Figure 8 shows the different machine position modes and according to the experimental and simulation data comparison in Figure 9, when analyzing the dynamic characteristics of the machine tool in a static state, the compared data have small differences. The error between the natural frequencies obtained from the experiment and those obtained from Ansys-Workbench finite element modal simulation is approximately between 3% and 12%. The error value is relatively small. Therefore, it can be proven that the accuracy and effectiveness of the established model of the dual-rotary five-axis machine tool, which can be used for modal analysis of the machine tool.

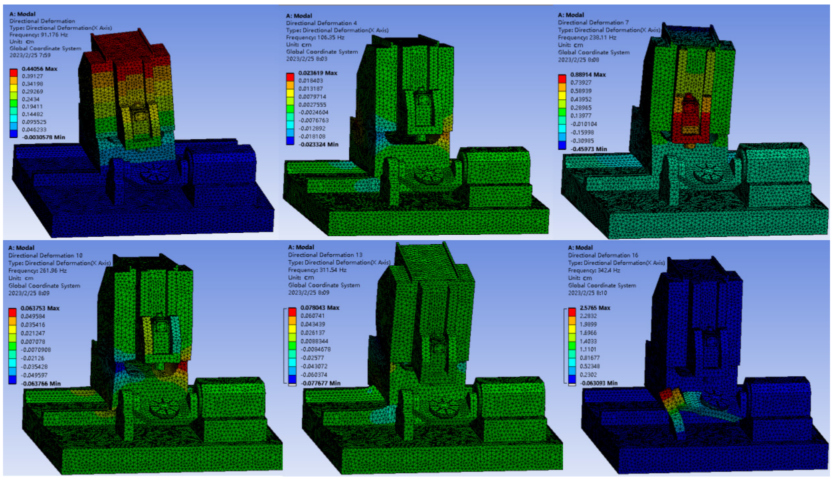

Figure 7. Modal simulation of machine tool at the same pose.

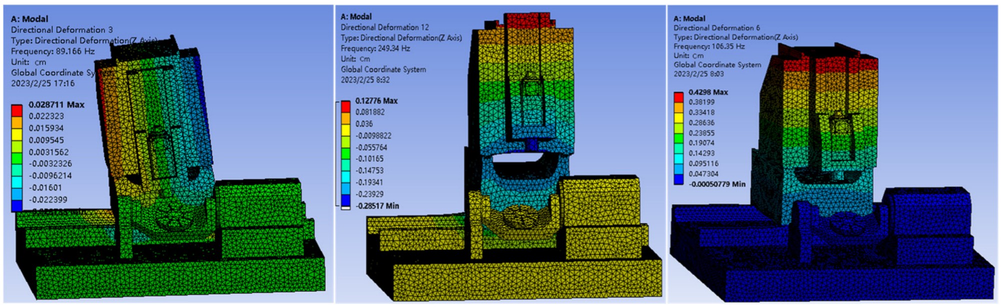

Figure 8. Different machine position modes.

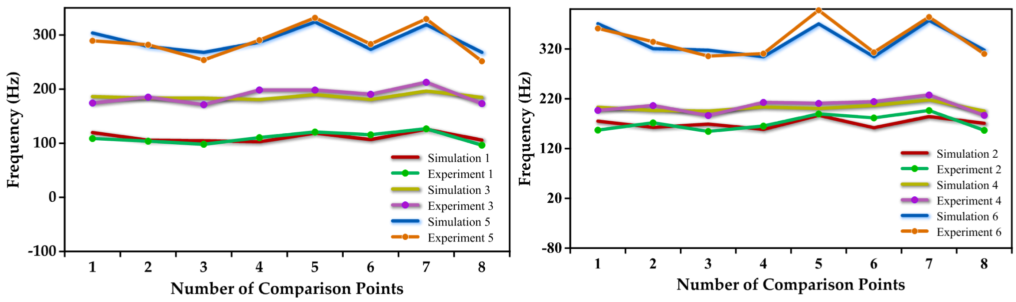

Figure 9. Comparison between simulation and experiment.

4.2. Knowledge Base Server Construction and Tool Path Evaluation Algorithm Embedding

The algorithm server of the digital twin system is built on the Django framework and serves as the implementation of the knowledge base processing unit of the digital twin system. This server is a key component in forming a closed loop between the data and knowledge base of the digital twin system. It can analyze various data and connect them to the modal system of the machine tool. Additionally, by integrating with big data algorithm frameworks such as Flink, it can perform real-time streaming computation on the collected data.

4.2.1. Embedding Three Types of Kriging Algorithms into the Knowledge Base

For multi-axis high-speed machining of weakly rigid thin-walled parts, during the movement of machine tool components in the entire workspace, the structural characteristics, relative spatial positions, and coupling force vectors of each part of the machine tool are time-varying. Therefore, the dynamic characteristics of each position point in the workspace of the machine tool are different at different times. After obtaining the discrete dynamic characteristic data of the machine tool through experimentation or simulation, the Kriging algorithm can be used to obtain the dynamic characteristic data of the machine tool in the entire machining space [34].

Collected simulation information of 125 machine tool position points in the processing area, and then used Kriging interpolation to interpolate them. After converting the Kriging algorithm into code and embedding it into the digital twin system, the input variables, such as tool path and cutting amount, are used as input variables of the digital twin system for calculation, and the evaluation results of the tool path are obtained, which provides data support for the machining parameter optimization module. Figures 10 and 11 show the calibration diagrams of the dynamic characteristics spectrum of the machining space generated based on the collected data.

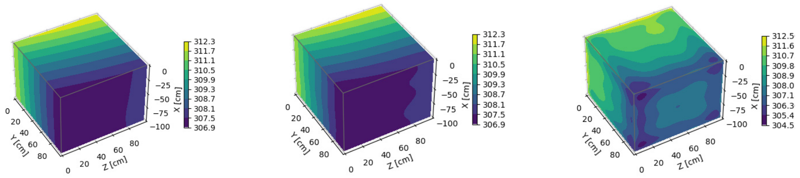

Figure 10. Three different modal fields generated by kriging.

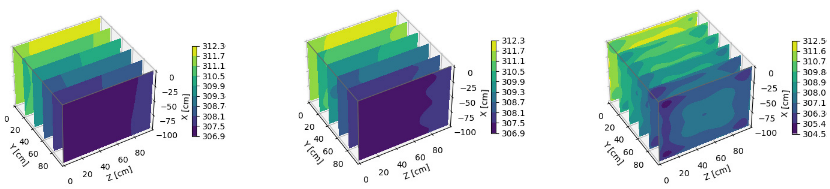

Figure 11. Three different kriging modal field slices.

4.2.2. Cutting Parameter Optimization Algorithm Embedded in Knowledge Base

The specific process is shown in Figure 12, and the main optimization objectives are the machining chatter error and the inherent frequency of the machine tool. The specific optimization parameters are spindle speed, spindle feed rate. The fitness of each chromosome is obtained through the evolutionary knowledge base and evaluation rule function of the digital twin.

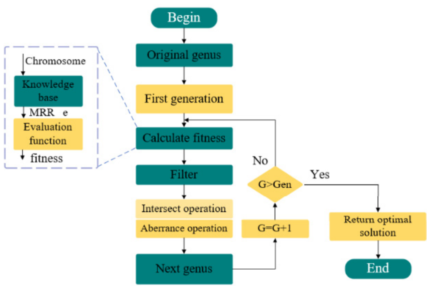

Figure 12. Flow chart of genetic algorithm.

Also, according to literature [35], the relationship between machine tool chatter frequency f_a and cutter tooth passing frequency f_c is:

$$\left[\begin{array}{c} \frac{f_a}{f_c} = T + \frac{\varepsilon}{2\pi} \\ f_c = nN \end{array}\right. \tag{1}$$

where: N is the number of cutter teeth; n is the spindle speed; ε is the phase displacement difference between adjacent cutter tooth machining surfaces; T is an integer of another $\frac{\varepsilon}{2\pi} < 1$.

It can be seen from Formula (1): when $\varepsilon = 2\pi$, chatter in the machining process of the machine tool can be avoided, whereby the different natural frequencies $f_\zeta = f_a$ of the machine tool that vary with the spatial position during the machining process can be obtained, and under the conditions of $\varepsilon = 2\pi$, the spindle rotation speed n that avoids chatter in the machining process of the machine tool can be obtained. The expression is:

$$n = \frac{f_\zeta}{N(T+1)} \tag{2}$$

Therefore, the spindle rotation speed obtained by Formula (2) under different natural frequencies and the parameters after this optimization will be tested and verified.

Based on the research mentioned above, the optimization information is digitized using the digitalization module and transmitted to the physical space for multi-axis CNC machining optimization.

4.3. Visualization Interface of Processing Unit Digital Twin System

The digital twin scene of the CNC machine tool is developed using the Unity engine and communicates with the algorithm server through the HTTP protocol, leveraging Unity's web module. Meanwhile, the UI operating interface is designed based on the production environment and algorithm factors. Figure 13 shows the visualization interface of the digital twin system for the machining unit.

Figure 13. Digital visualization interface for machine tool processing.

4.4. Cutting Experiment Verification

The workpiece blank is made of 7075 hard aluminum alloy, and the fixture used is a commonly used self-centering three-jaw chuck. The cutting tool is a four-bladed tapered ball head cutter, which specific parameters are detailed in Table 3. The experimental process in this article is the side milling finishing process. The control group processing parameters are a speed of 8000 r/min, a feed per tooth of 0.0625 mm, a feed speed of 2000 mm/min, and a cutting depth and cutting pitch of 0.2 mm each. The experimental group's processing parameters, after parameter optimization, are a speed of 9200 r/min, and a feed per tooth of 0.0313 mm, while the cutting depth and cutting pitch remain unchanged.

Table 3. Processing tool parameters.

Tool	Bilateral Angle (°)	Tool Nose Radius (mm)	Tool Diameter (mm)	Blade Length (mm)	Cutter Length (mm)	Blade Count
Conical Ball end Cutter	4	1.5	7	59	218	4

The optimal 16 measurement points (highlighted in red) were selected on the tested blade, as shown in Figure 14. Next, the impeller was fixed on the coordinate measuring machine (PMM-C) measurement table, as shown in Figure 15. The overall impeller measurement steps for PMM-C are as follows: (1) Place the impeller on the turntable; (2) Establish the impeller coordinates; (3) Edit the individual blade detection program; (4) Add turntable blade rotation instructions to the program; (5) Use the embedded PC-DMIS to complete the measurement; (6) After the inspection is completed, output and print the report.

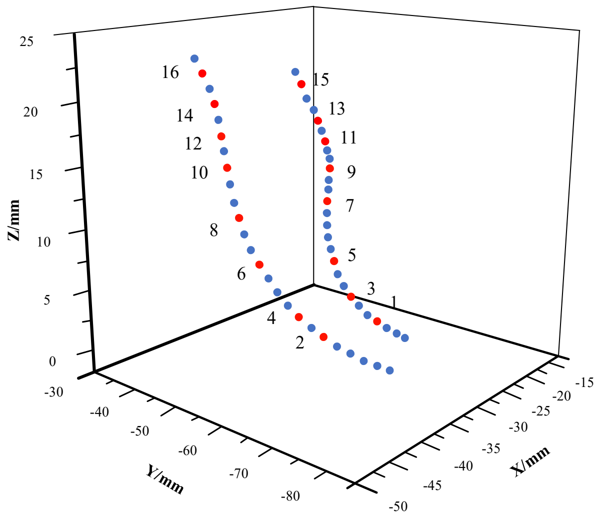

Figure 14. Comparison of profile error detection before and after optimization.

Figure 15. Impeller measuring machine tool Leitz PMM-C.

Finally, the blade was measured according to the measurement procedure. Since the blade is thin and may deform during the machining process, a margin of 0.2 mm was reserved, and the tolerance of the measurement points was set to ± 0.2 mm. The measurement data are shown in Tables 4 and 5.

Table 4. Measured roughness values of impeller before optimization.

No	Measured Value/mm			Status	No	Measured Value/mm			Status
	X	Y	Z			X	Y	Z	
1	−35.7542	−71.4724	14.7275	Pass	9	−45.6457	−44.7441	34.2733	Pass
2	−36.5741	−71.2224	17.1114	Failed	10	−42.7587	−43.5744	36.7548	Pass
3	−37.4242	−61.0441	19.5853	Pass	11	−42.4755	−47.6842	37.3387	Pass
4	−37.4524	−60.2742	21.5781	Failed	12	−41.0445	−48.3775	38.3211	Pass
5	−39.7524	−54.4553	21.5334	Pass	13	−38.7527	−49.7566	39.5283	Pass
6	−41.2424	−51.7252	24.5745	Pass	14	−40.7674	−52.1141	41.3347	Failed
7	−43.4277	−48.5524	27.4228	Pass	15	−36.8333	−59.4769	43.2344	Pass
8	−45.3633	−50.4566	32.7527	Failed	16	−38.6787	−62.0775	46.3679	Failed

Table 5. Measured roughness values of impeller after optimization.

No	Measured Value/mm			Status	No	Measured Value/mm			Status
	X	Y	Z			X	Y	Z	
1	−34.7561	−70.0465	14.1042	Pass	9	−43.3906	−42.1025	33.4213	Pass
2	−35.1352	−69.0652	17.7841	Pass	10	−45.7952	−42.0489	35.0569	Pass
3	−37.3987	−64.1038	20.4408	Failed	11	−44.3619	−45.3721	38.1146	Pass
4	−35.4621	−57.1854	19.7619	Pass	12	−43.4216	−46.0981	37.4102	Pass
5	−40.6872	−54.3278	23.3561	Failed	13	−37.3069	−47.8742	39.3964	Pass
6	−40.9042	−50.6531	24.7848	Pass	14	−37.7632	−48.5631	40.9451	Pass
7	−42.1104	−48.7758	27.2246	Pass	15	−35.4211	−58.3964	43.0196	Pass
8	−43.0138	−48.6653	30.0193	Pass	16	−36.0145	−60.0047	45.8745	Pass

Based on the experimental results in Figure 16, it can be seen that the surface quality of the workpiece after optimizing the machining parameters is smoother and has fewer visible defects compared to the control group. The experimental results indicate that the machining parameters obtained through the optimization model have improved the surface quality of the impeller blades.

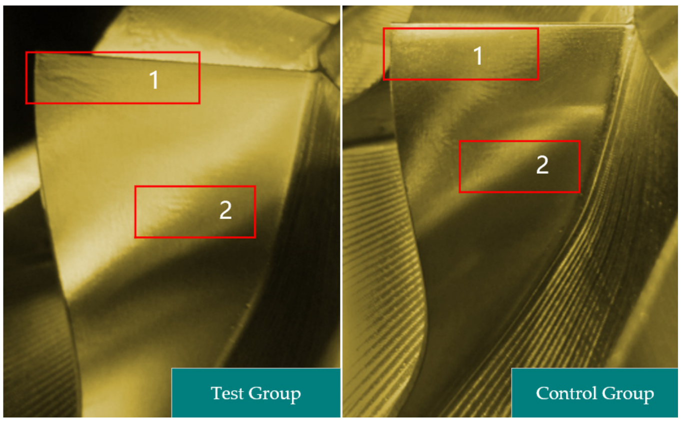

Figure 16. Blade surface before and after optimization and areas 1 and 2 in the figure are the main measurement areas.

In Figure 17, the blue curve represents the workpiece contour error detection data for the control group under the machining parameter experiment, and the red represents the detection data for the experimental group. As can be seen from the figure, for the blade that has not undergone optimization of multi-axis coordinated machining error evaluation and control method based on digital twin technology, the maximum machining contour deviation of the blade is 0.2333 mm, and the overall contour error polyline has a steeper and more tortuous slope. However, for the blade detected after optimization of multi-axis coordinated machining error evaluation and control method based on digital twin technology, the maximum contour deviation of the blade is 0.2298 mm, Meanwhile, as shown in Table 5, the pass rate has increased from 68.75% to 87.5%.and its overall contour error polyline has a flatter slope. It can be concluded that the average contour error of the blade detected after optimization of multi-axis coordinated machining error evaluation and control method based on digital twin technology is reduced by 18.75%. Therefore, it can be seen that the proposed method of multi-axis coordinated machining error evaluation and control based on digital twin technology can effectively improve the surface quality of the workpiece.

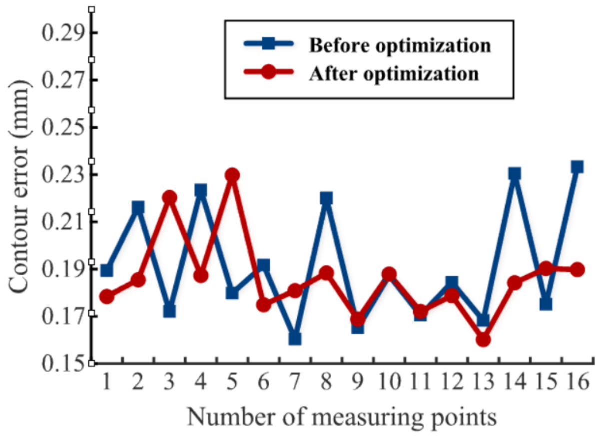

Figure 17. Comparison of profile error detection results before and after impeller optimization.

5. Conclusions

1. In response to the intelligent processing needs of aviation thin-walled parts, a dynamic characteristic digital twin system building method for thin-walled machining units was proposed by combining digital twin technology and microservice technology. The method aimed to gradually build a complete information communication process starting from data collection, transmission, and processing, and to reduce system coupling as much as possible from the design stage of the twin system.
2. By simulation and experimental methods, dynamic characteristic data at different positions and orientations of the machine tool were obtained, and the dynamic data were used as the input of the digital twin system to support the optimization of thin-walled machining parameters. On the basis of the established data loop of the digital twin system, the Kriging method was used to analyze the change rules of the relative spatial position of the machine tool spindle and the swivel table angle by establishing a knowledge base for calibrating the time-varying dynamic characteristic spectrum of the machine tool, and a set of evaluation and optimization strategies based on the digital twin system was proposed for thin-walled machining.
3. A traceable optimization scheme for thin-walled machining parameters and processes was proposed for poorly machined areas, and the maximum deviation of the machining contour of the impeller was reduced from 0.2333 mm to 0.2298 mm after optimization. The average machining contour error of the impeller detected after the proposed method optimization was reduced by 18.75%, which verified the effectiveness of the proposed method.

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