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Optimization Method of CNC Machining Parameters Based on Digital Twin

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Abstract. This article mainly discusses the optimization methods of machining parameters for CNC machine tools. Firstly, based on the functional requirements and application scenarios of CNC machining, three-dimensional modeling and motion simulation of twin machine tools are achieved, and a data-driven cutting process model is constructed. Then, in the actual production process, in addition to ensuring the normal processing of physical equipment such as CNC machine tools, the design of data perception schemes and the layout of data acquisition equipment during the processing were also completed, providing data support for information exchange between digital twins and real equipment. In terms of data transmission, the operation data of the entire CNC machine tool processing process is collected through the data perception layer equipment, and all perception data is then uploaded to the virtual space through the communication network of the transmission layer to drive the twin model for subsequent simulation, optimization, and prediction. Finally, based on the results of data collection, an objective function that needs to be optimized was established in the optimization process of CNC machining parameters. The objective function takes the total processing time and processing cost as optimization objectives, and an improved bee colony algorithm is used to solve the objective function. Through experimental simulation, it has been found that the use of CNC machine tool processing parameters can improve both time and processing costs, and the optimization results meet the design expectations.

Keywords: digital twin, parameter optimization, bee colony algorithm, CNC machining

1 Introduction

Compared with traditional manual processing, CNC technology has the characteristics of high efficiency, high precision, high degree of automation, and good flexibility and compatibility, thus playing a crucial role in the era of intelligent manufacturing. In recent years, CNC technology has undergone changes with the transformation of advanced manufacturing concepts. Advanced manufacturing concepts have evolved from closed, large-scale, and single manufacturing models to open, lightweight, and integrated directions. At the same time, the introduction of advanced technologies such as intelligent operation, online monitoring, fault diagnosis and elimination in the manufacturing process has made modern CNC machining more humane [1].

Curved surfaces are a typical feature of machining. In other manufacturing fields such as aerospace and automotive, with the improvement of machining technology, more complex curved parts are designed and produced, and have been widely used, such as aircraft engine impellers, ship thrust turbine blades, automotive sheet metal parts, robot casings, etc. In the process of surface machining, three-axis or five axis CNC machines are currently the most commonly used equipment for complex surface machining. CNC machines ensure machining quality and accuracy by accurately controlling the relative motion between the tool and the workpiece. However, different machining objects and different machining processes for the same machining object are often complex and diverse. Therefore, it is necessary to fully consider factors such as the motion trajectory and energy consumption of the tool head in the designated machining process and the control process of the CNC machine tool. Therefore, reasonable path planning and machining process parameter design can minimize production costs, improve the CNC machining accuracy and efficiency of curved workpieces [2].

The machining process parameters are the control variables for the multi-objective optimization process of

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CNC machining. If the selection of process parameters is not appropriate, it is difficult to ensure the optimal machining objectives, and it can also lead to problems such as tool damage, part scrapping, and machine tool failure caused by improper cutting force. Therefore, the selection of CNC machining process parameters largely determines the quality of the machining results. However, traditional processing parameters lack intelligence, optimization methods have shortcomings, and efficiency is low, mainly reflected in the following three aspects [3].

1) The process parameters of CNC machining are generally selected based on empirical mathematical models and process manuals, which are not related to historical data. However, according to big data analysis theory, the support of historical processing data can quickly obtain process plans before production. In order to avoid collision between cutting tools and machine tools, the selected processing parameters are relatively conservative and not sufficient to fully exert the best performance of the machine.

2) The optimization algorithms for CNC machining parameters used in traditional methods often have insufficient accuracy in solving problems, leading to the erroneous selection of more excellent process parameter schemes.

3) The traditional parameter optimization model is static, while actual machining is dynamically changing. Under the interference of disturbance events such as machine tool vibration, cutting heat, and tool wear, the machining state of the machine will dynamically change with the continuous progress of the machining process. Static algorithms cannot adapt to dynamic changes, so optimization results are often not applicable.

In response to the above situation, this article focuses on the optimization of cutting process parameters for CNC machine tools as follows:

1) We have established a digital twin model for CNC machine tools to collect machining data, and a large amount of machining process data can serve as the training basis for intelligent optimization algorithms;

2) Constructing a mathematical model for the machining process of CNC machine tools with time and productivity as optimization objectives;

3) Improving the bee colony algorithm to solve the constructed model.

2 Related Work

Parameter optimization is a research topic that should be involved in every processing scenario. Domestic and foreign scholars have made relatively many achievements in optimizing processing parameters. This article lists some research results and proposes the research direction based on the research of various scholars.

Shasha Zeng proposed a machining process parameter optimization method based on the backpropagation neural network method, with the aim of optimizing the milling process parameters of thin-walled parts. Firstly, a signal-to-noise ratio predictor for thin-walled part milling was established, and by maximizing the signal-to-noise ratio, the dynamic variation of the milling process was minimized, and the optimal combination of CNC machining process parameters was found to obtain the optimal machining result [4].

Yuanchao Ni optimized the cutting force and cutting process parameters in the machining of turbine teeth, established a mathematical model of the machining process, and then used finite element analysis method and orthogonal experiments to optimize the machining process parameters of the tool based on the mean cutting force, amplitude, and cutting heat amplitude of the tool. The optimization results of the machining parameters that affect the cutting force, cutting heat, and cutting depth of the tool were obtained [5].

Guowan Yang established solid models of workpiece gears and turning tools based on the kinematic principles of gear turning process. Then, the response surface method was used to establish a main cutting force prediction model, and important machining parameters such as cutting speed and feed rate were analyzed. Finally, the target Jupiter was optimized using genetic algorithm to obtain the optimal machining parameters. The rationality of the machining parameters was verified in practical applications [6].

Tong Yao, the research object is ultra precision machining of monocrystalline silicon, with machining parameters as spindle parameters. Through optimization of the established parameter weight model, the spindle speed, feed rate, and cutting depth are ultimately set, and high-quality monocrystalline silicon components with surface roughness can be obtained in practical machining applications [7].

Qi Qi, through in-depth analysis of the cutting process, identified various factors that affect the cutting effect, established a cutting parameter optimization model, and used genetic algorithm in MATLAB to calculate and simulate the mathematical model, obtaining the optimal CNC machining cutting parameters. Finally, the feasibility of the method was verified through simulation experiments [8].

Zhi Liu, in order to solve the problem of designing key process parameters in CNC machining process under uncertain environment, comprehensively considered the uncertainty of tool service life and the decision-making of cutting speed and feed rate. When establishing the objective function, a nonlinear programming model for CNC machining process parameters was established with the goal of minimizing cutting process time. Then, based on the uncertainty of the model, a robust optimization method was adopted to establish the corresponding robust equivalent model. The feasibility of the robust model was verified through examples, and the changes in uncertain parameters were analyzed, indicating that the decision-making of the robust model is practical and effective [9].

Pengcheng Zhao from China Coal Group has improved the processing quality of ultrasonic vibration cutting technology and reduced the surface roughness of workpieces. Firstly, a mathematical model was established between the surface roughness of workpieces processed by ultrasonic vibration cutting and the spindle speed, cutting speed, feed rate, and ultrasonic amplitude. The process parameters that affect the surface roughness of workpieces processed by ultrasonic vibration cutting were optimized. Then, using more curved surface corresponding methods, a second-order response model for ultrasonic vibration cutting of 45 # steel was established. The roughness model of ultrasonic vibration cutting of 45 # steel was fitted through central composite experiments. Finally, the 3D response surface diagram of the surface roughness of the ultrasonic vibration cutting workpiece was used to analyze the interaction effect of various process parameters on surface roughness. Genetic algorithm was applied to optimize the machining parameters, and the more suitable cutting amount was selected and verified through further experiments. The results show that the optimal combination of various process parameters is: spindle speed is 70.95 m/min, cutting speed is 0.11 m/min, feed rate is 0.95 mm/r, ultrasonic amplitude is 26.80 mm. The optimized parameter combination improves the machining quality [10].

Based on the above research results, this article proposes a parameter optimization scheme for CNC machine tools based on digital twins, starting from practical applications. This makes the parameter optimization process more visual and intelligent, thereby improving machining accuracy. The chapter composition of this article is as follows:

Chapter 3 mainly discusses the construction process of a digital twin model based on CNC machining process, including the construction of the overall framework, the implementation process of data collection and mapping, and the implementation of necessary functions at the data and simulation level. Chapter 4 mainly focuses on the process of parameter optimization. Firstly, a multi-objective optimization function for the machining process is established. For solving the objective function, this paper uses an improved bee colony algorithm and obtains parameter results. Chapter 5 is the simulation phase, using the parameters obtained in Chapter 4 for simulation processing to obtain the results of processing cost and processing speed. Chapter 6 is the conclusion section, which summarizes the research results of this article and provides prospects for future development.

3 The Process of Establishing a Digital Twin Model

This section discusses the establishment of a digital twin machine tool model for optimizing cutting parameters. Digital twin is a technology that utilizes physical models, sensor updates, operational history, and other data to integrate multi-disciplinary, multi physical, multi-scale, and multi probability simulation processes to complete mapping in virtual space, thereby reflecting the entire lifecycle process of corresponding physical equipment. Digital twin can be seen as a digital mapping system for one or more important and interdependent equipment systems. It is a universally applicable theoretical and technical system that can be widely applied in product design, manufacturing, medical analysis, engineering construction, and other fields. The architecture of digital twins includes five levels: user domain, digital twin, measurement and control entity, real industry physical domain, and cross domain functional entity. The application scenarios of digital twin technology are extensive, including but not limited to intelligent manufacturing, water management, and other fields. Through methods such as virtual real interaction feedback, data fusion analysis, and decision iteration optimization, new capabilities are added or expanded for physical entities.

Therefore, based on existing technological means and data collection and analysis, in order to achieve three-dimensional modeling and motion simulation of twin machine tools, this chapter constructs a data-driven cutting process model. Based on the analysis of the processing requirements of the existing intelligent manufacturing workshop, in addition to ensuring the normal processing of physical equipment such as CNC machines, the actual processing process also needs to perceive the data during the processing [11]. The main purpose is to provide data support for information exchange between digital twins and real equipment. During the machining process, the operational data of the CNC machine tool is collected through the data perception layer device. All perception data is then uploaded to the virtual space through the communication network of the transmission layer to drive the twin model for subsequent simulation, optimization, prediction, and other behaviors. Therefore, this section discusses the construction process of the digital twin model.

3.1 Overall Framework of Digital Twin CNC Equipment

When building a digital twin framework, the following guidelines should be considered and followed: the digital twin framework should be able to accurately simulate and reflect the machining process of CNC machine tools, achieving bidirectional mapping of information in virtual and real spaces. At the physical level, it is necessary to collect various types of data during the processing, so corresponding sensors need to be arranged at the collection object to achieve comprehensive perception of multi-source heterogeneous data during the processing. During the machining process, the cutting parameters, spindle speed, and tool information of the CNC equipment will be collected through the data perception layer, uploaded to the virtual space through communication networks such as Ethernet, and finally monitored and predicted in the model. Therefore, the overall framework model is shown in Fig. 1.

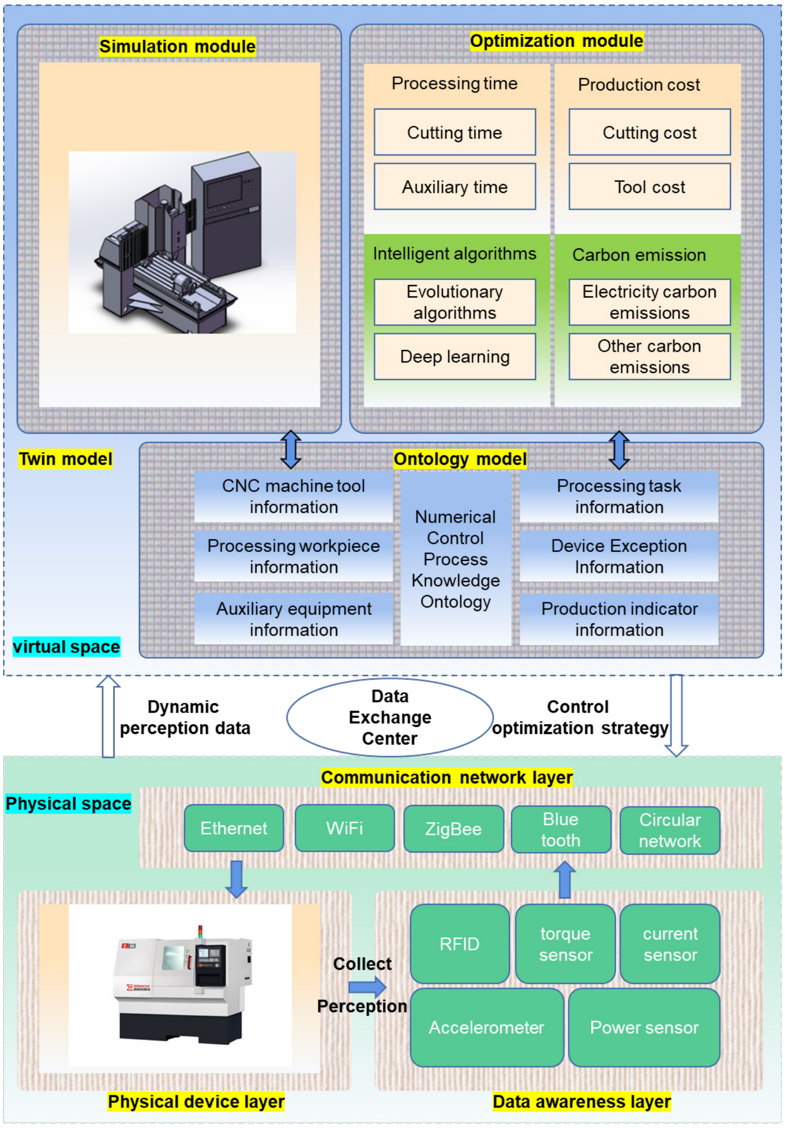

Fig. 1. The overall framework model of digital twin machine tools

The framework reflects the structure of the entire system, and the functions of each module are expanded based on this structure. In physical space, in addition to having physical equipment such as CNC machines to ensure normal processing, it is also necessary to have a comprehensive perception of multi-source heterogeneous data during the machining process, providing data support for information exchange in virtual and real spaces. During the machining process, the actual operating status of the CNC machine tool will be collected and sensed through various sensing devices in the data perception layer.

All perception data will be uploaded to the virtual space through communication networks such as Ethernet, WiFi, ZigBee, etc. to drive the twin model for subsequent simulation, optimization, prediction, and other behaviors. In virtual space, the main function is to accurately map the production behavior in physical space, which consists of ontology model and twin model. (1) The ontology model is the link and bridge between physical space and virtual space to achieve information exchange. It uses network native language for unified formal description, ensuring consistency and accuracy of information exchange. This ontology model can perform semantic analysis on physical perception data to drive intelligent simulation of twin models; At the same time, the ontology model can parse the optimization strategies in the twin model into CNC instructions to ensure that the optimization strategies can be effectively executed by the physical machine tool. (2) The twin model is the core module of the entire framework, consisting of a simulation module and an optimization module. Among them, the simulation module can synchronously simulate the machining behavior of physical machine tools in multiple dimensions such as geometry, physics, and functionality, such as the movement process of cutting tools and the removal process of material debris. It can also accurately verify the effectiveness of machining optimization strategies.

The data exchange center is located between the physical space and the virtual space, and is the foundation for ensuring the normal operation of the twin system. It mainly includes perception data generated by physical processing and control optimization strategy information generated by virtual simulation optimization. On the one hand, based on perceptual data, the processing status can be accurately obtained, providing a rich data source for dynamic optimization of processes; On the other hand, the optimization strategies generated by virtual space can guide physical machining and ensure the normal operation of machine tools.

3.2 3D Modeling and Data Mapping of CNC Machine Tools

The digital twin geometric model of CNC machine tools refers to a digital model expressed in digital space that is consistent with the three-dimensional geometric features, spatial topological relationships, and other physical entities of CNC machine tools [12]. The construction process of its digital twin geometry model is shown in Fig. 2.

In the process of constructing digital twin geometric models, in order to simplify the complexity of the model itself and highlight the role of data, it is not necessary to consider the damping, elastic deformation and other characteristics of its mechanical components in the model, and only consider it as a rigid body.

The construction of each component in the model can be divided into two ways: for standard parts, they can be imported from the software's standard parts library, and then instantiated based on the actual dimensions of the parts to obtain personalized components about CNC machine tools. For non-standard parts, use functional expressions to represent the dimensions of their important feature parameters and the correlation between important feature parameters, and then perform feature modeling on the three-dimensional geometric model of the established non-standard parts of CNC machine tools.

By combining the assembly relationship and motion feature relationship between components, a digital twin model of components and a digital twin model of components can be established. When constructing the digital twin model of each level component of CNC machine tools, parameterize the partial features of the component digital twin model. By assembling and combining various hierarchical models in the same way, a hierarchical digital twin geometric model of the CNC machine tool can be established. When modeling various components, this article uses Solidworks 3D modeling software to complete the modeling [13], and then imports the generated assembly model into the twin system. The specific model is shown in Fig. 3.

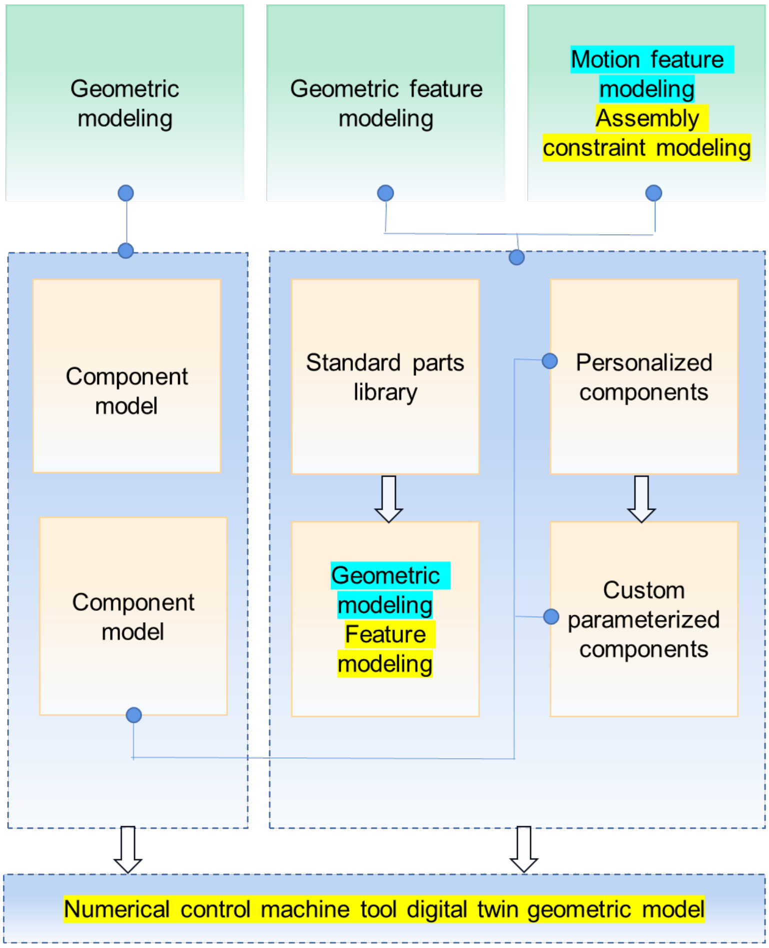

Fig. 2. Process diagram for constructing digital twin geometric models

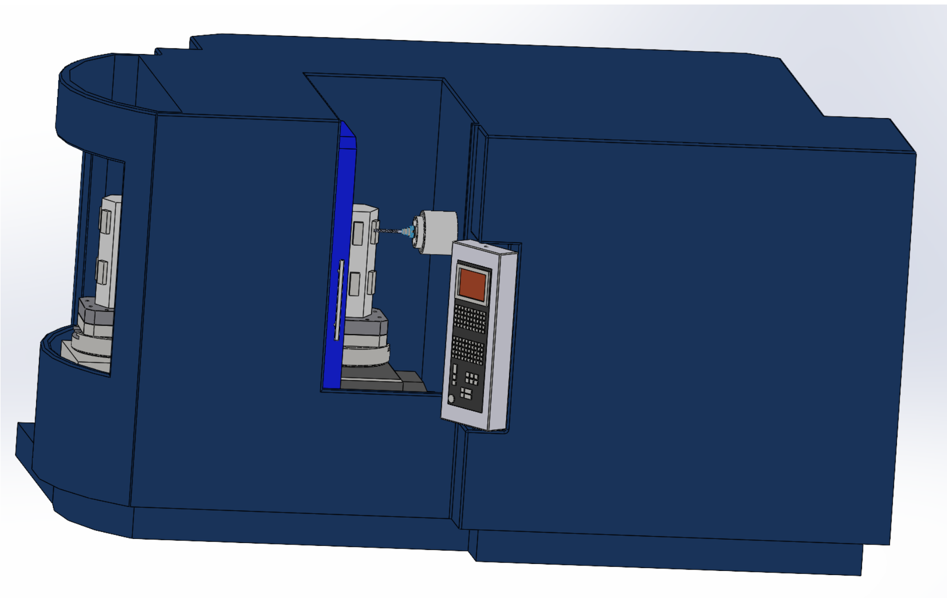

Fig. 3. CNC machine tool model

This article takes the modeling of Baoji Machine Tool Company CNC machining center as an example. Firstly, SolidWorks tool is used to 3D model the various components of the CNC machine tool, and the assembly relationships between the components are established to construct the assembly model of the CNC machine tool. Then, WRL format virtual reality text format files are exported, and then imported into 3Ds Max for 3D rendering.

For data collection in the machining process of machine tools, it is necessary to collect the real-time status of the machine tool to ensure its good operating status. The real-time data collection of machine tools mainly utilizes multi-source heterogeneous data from the machining process of the machine tool. The sources of multi-source heterogeneous data include the working status of the CNC machine tool itself, workshop scheduling, and workshop processing auxiliary equipment. Fig. 4 shows the hierarchical relationship between the various components of the CNC machine tool digital model.

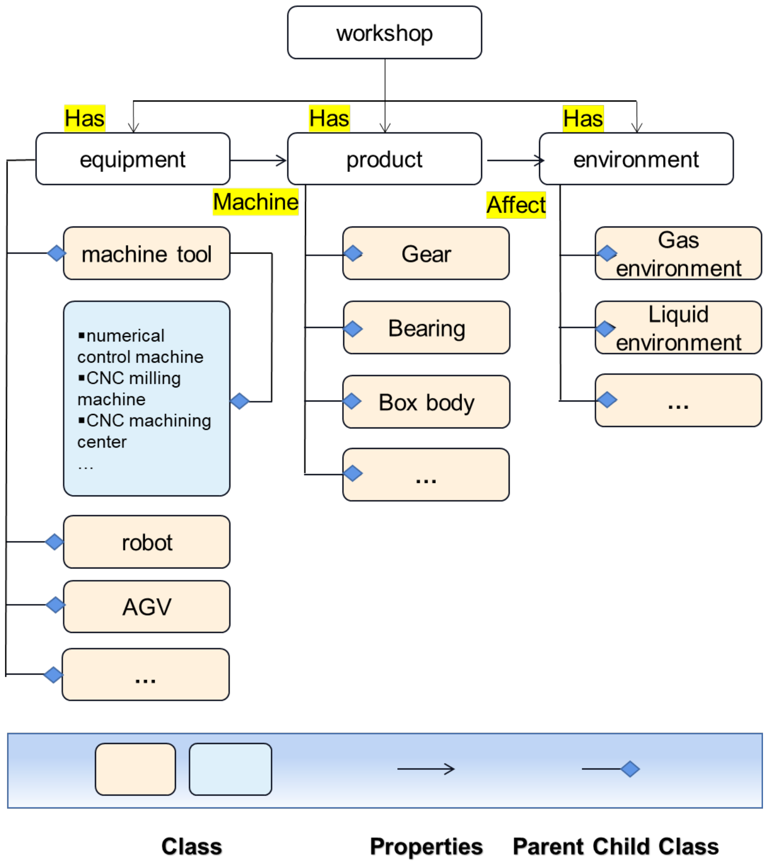

Fig. 4. Functional relationship diagram between various modules

1) CNC machine tools: including basic information of CNC machine tools, component status information, operating status information, alarm information, tool information, and machining quality information.

2) Scheduling: mainly includes information on workpiece materials and warehouse inventory. The material information of the workpiece includes material properties, quality requirements, and other information. Warehouse inventory mainly includes information such as workpiece inbound and outbound.

3) Auxiliary equipment: mainly includes information on related auxiliary equipment such as robots, AGV cars, air compressors, oil coolers, etc., including basic information and technical parameters of auxiliary equipment.

4) Other: including environmental information and digital materials. Environmental information includes temperature, humidity, atmospheric pressure, and other information. Digital data refers to digital descriptions of physical equipment and workshops, such as three-dimensional geometric models of equipment.

3.3 Numerical Control Machine Tool Motion Simulation

The motion model of CNC machine tools has a corresponding hierarchical structure. The motion of higher-level components will cause changes in the position of lower level components, while the motion of lower level components will not affect the spatial position of higher-level components. Construct a motion model hierarchy tree as shown in Fig. 5, with the hierarchical relationships between core motion components in descending order: X-axis motion block → Y-axis motion block → Z-axis motion block → spindle motion block → workpiece. Among them, the X-axis motion block mainly includes the Y-axis motion block, crossbeam, slider, and left and right columns, while the Y-axis motion block is composed of the Z-axis motion block and slider, etc. The Z-axis motion block mainly includes the spindle motion block [14].

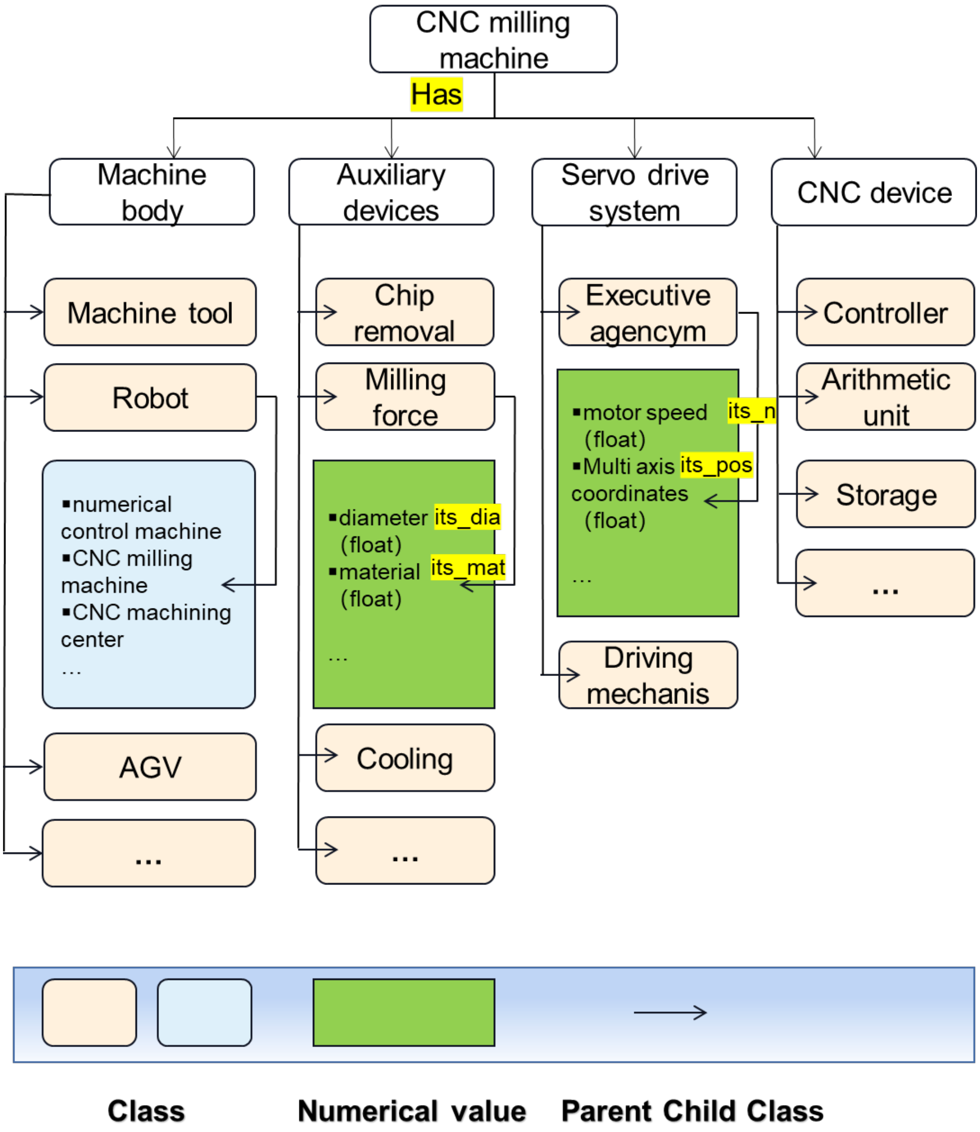

Fig. 5. Motion model hierarchical tree

Analyze useful machining parameters and instructions from CNC codes to drive the motion components of twin machine tools for motion simulation. The process of NC code parsing in Fig. 6 mainly includes four steps: NC verification, NC conversion, speed adjustment, and interpolation operation.

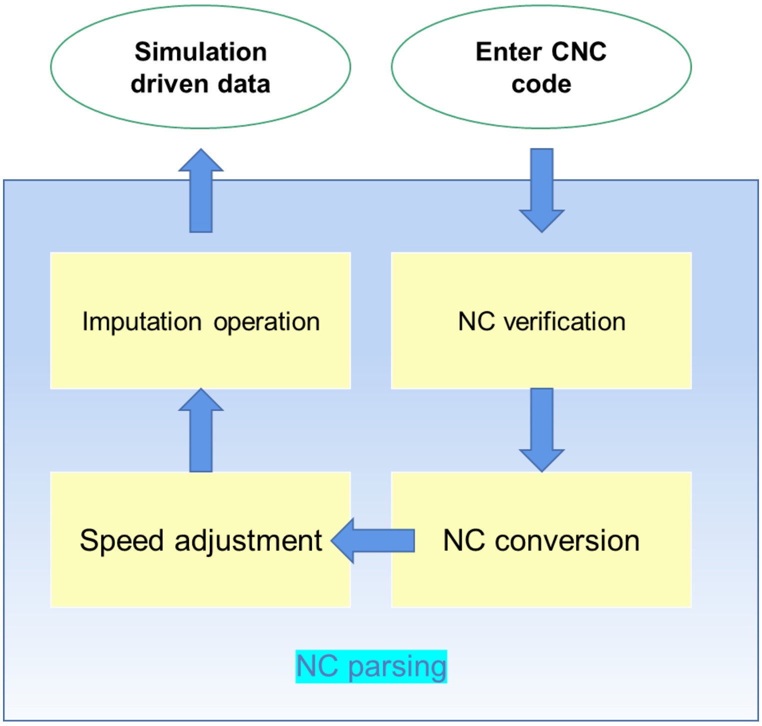

Fig. 6. The process of CNC code parsing

Step 1: NC verification, which verifies the syntax of the CNC code to determine whether it meets the basic syntax rules. If it does not, an error message is recorded and an error prompt is displayed on the system interface.

Step 2: NC conversion, which converts various instructions in CNC code into standard code formats, including linear interpolation and circular interpolation.

Step 3: Speed adjustment. In virtual machining, when the tool's motion speed changes, the path segment for controlling tool acceleration and deceleration can be appropriately increased to ensure that the tool can work smoothly during machining.

Step 4: Interpolation operation, based on time division method, interpolates each path segment to obtain the position and velocity of the starting and ending points of each interpolation segment on the outer edge of the workpiece.

Taking linear interpolation in a three coordinate system as an example, given a certain program segment in CNC machining, with a starting point of P_1 and an ending point of P_2, the length of the machining path is:

$$S = P_2 - P_1. \tag{1}$$

Assuming the interpolation period is T, the current interpolation period is i, the current position is P_d, and the distance from the starting point is expressed as:

$$S_d = P_d - P_1. \tag{2}$$

The feed rate in cycle $i+1$ is v_j, and the displacement in cycle $i+1$ is L_{i+1}. The distance between the position P_{i+1} and P_1 at this time is:

$$L_{i+1} = L_i + \Delta L. \tag{3}$$

$$P_{i+1} = P_i + \left(P_2 - P_1\right) \times L_{i+1} / L. \tag{4}$$

The offset of each axis during the $\mathrm{i}+1$-th interpolation cycle is:

$$\Delta P_{i+1} = P_{i+1} - P_i. \tag{5}$$

Perform motion simulation according to the above method, continuously cycling back and forth until the entire machining process is completed. This method can ensure that the machining trajectory is relatively smooth and can meet the requirements of simulation accuracy.

After the above analysis, the digital twin framework required in this article has been constructed, and key technical aspects such as data collection and transmission have been described. The digital twin model is the foundation of the entire system, and parameter optimization methods, processing status monitoring, etc. are all run on the basis of the digital twin model. The digital twin model establishes the foundation for subsequent parameter optimization.

4 Process Parameter Optimization Process

This section mainly describes the optimization process of CNC machining parameters, which mainly includes two aspects. Firstly, the objective function that needs to be optimized is established. This article takes the total processing time and processing cost as the optimization objectives. Then use the bee colony algorithm to solve the optimization objective function [15]. In actual machining, the selection of cutting parameters often has a significant impact on cost and energy consumption. High production costs and low processing efficiency undoubtedly pose enormous economic pressure on manufacturers. In order to improve economic and environmental benefits, this chapter mainly studies the optimization methods of cutting parameters by improving CNC machining efficiency and reducing production costs. CNC machining is an important mechanical processing method, including milling, which is currently the most common machining process. Taking milling as an example, it can usually be divided into single pass milling and multi pass milling. Among them, single pass milling refers to completing the current machining task after one milling, which is suitable for processes with relatively small machining allowances, where the cutting depth is equal to the machining allowance. When the machining allowance is relatively large, if single pass milling is used, the cutting force may be too large, which can cause problems such as machine vibration and tool wear. Therefore, it is more reasonable to choose multi pass milling method. Establish a typical process flow for the machining process. In actual production, a single cutting process generally does not exist because general machining processes are difficult to complete in a single step. Multi pass milling is the process of dividing complex processes into multiple single pass processes to complete, usually combining rough machining with precision machining. In the rough machining stage, selecting a smaller cutting speed, larger feed rate, and cutting depth can quickly remove the blank, thereby improving production efficiency. In the precision machining stage, selecting a larger cutting speed, smaller feed rate, and cutting depth will result in less material being cut, but it can ensure the machining quality of the parts. In order to accurately analyze the CNC machining process curve, as shown in Fig. 7.

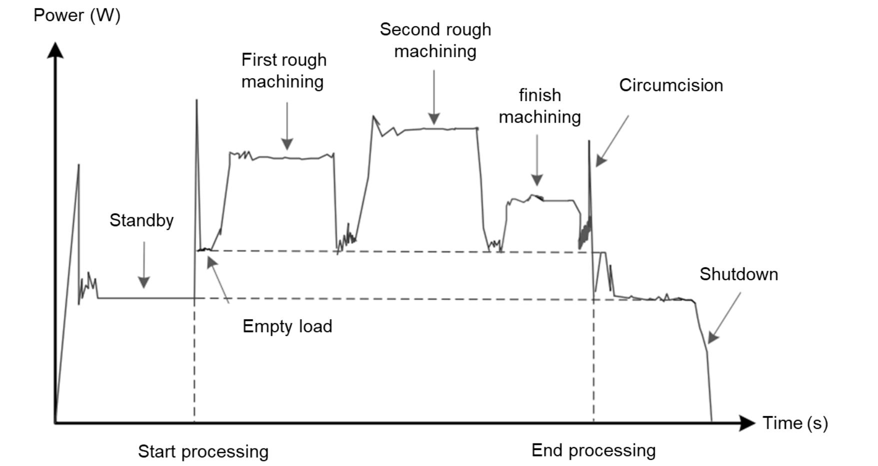

Fig. 7. CNC machining process curve

4.1 Establishment of Objective Function

Numerical control machining parameter optimization is a continuous function optimization problem with multiple constraints and nonlinearity. Establish a mathematical model for optimizing CNC machining parameters by determining the design variables, objective functions, and constraints of the problem [16]. Use v and t to represent the cutting speed and feed rate during the cutting process, and use t_h to represent the feed rate per tooth. Set the cutting parameters under stepless speed control during CNC cutting as continuous variables. Set the minimum production cost and maximum productivity as the optimization objectives for CNC machining parameters. The formula for the total CNC machining hours is as follows:

$$T_z = \sum_{i}^{n} T_{ci} + T_j + T_h + T_f . \tag{6}$$

In the formula, T_z represents the total time to complete the machining, T_{c_i} represents the time for the i -th rough machining, and the total number of rough machining times depends on the actual situation. T_j represents precision machining time, T_h represents tool change time, and T_f represents the total time for auxiliary processes such as no-load and tool return. The cutting time for rough machining is represented as follows:

$$T_{ci} = \left(\pi dl\right) / \left(1000 v t_h Z\right). \tag{7}$$

In the formula, d represents the cutting diameter, l represents the cutting length, v represents the cutting speed, Z represents the length of the tool, and t_h represents the feed rate of each tooth of the tool. The tool change time is represented as follows:

$$T_h = \frac{\pi l T_m}{1000 mC} v^{\frac{1}{m}-1} t_h^{\frac{1}{m}-1} Z^{\frac{u}{m}} d^{1-\frac{q}{m}} . \tag{8}$$

In the formula, T_m represents the tool change time caused by wear, and m, C, U, q are all the durability coefficients of the CNC machine tool. The representation of processing costs is as follows:

$$C_Z = T_Z\left(\frac{C_d}{T_d} + C_t + C_r\right). \tag{9}$$

In the formula, C_Z represents the total cost, T_Z represents the total time cost, C_d represents the prop cost, T_d represents the prop usage time, C_t represents the time management cost, C_r represents the labor cost, and the lowest processing time and lowest cost are used as optimization objectives, expressed as:

$$\min(T_z + C_Z). \tag{10}$$

4.2 Setting of Constraint Conditions

In the optimization problem of cutting parameters, a series of constraints need to be met, including the machining ability of the machine tool, the machining quality of the workpiece, the remaining life of the tool, etc., to ensure that the optimal cutting parameters can be searched within the allowable spatial range [17]. The constraint conditions are represented as follows:

1) Cutting parameter constraints:

$$v_{\min} \le v \le v_{\max}. \tag{11}$$

$$t_{\min} \le t_h \le t_{\max}. \tag{12}$$

2) Tool life constraints

$$T_d \ge T_{\min}. \tag{13}$$

3) Cutting power constraint

$$\frac{F_c v}{1000} \le \eta P_{\max}. \tag{14}$$

In the formula, F_c is the cutting force, η is the power coefficient, and $P_{\max}$ is the maximum power of the CNC machine tool.

4) Cutting force constraint

$$F_c \le F_{\max}. \tag{15}$$

4.3 Using Bee Colony Algorithm to Optimize the Target Model

The bee colony algorithm is inspired by the intelligent foraging behavior of bee colonies, which mainly includes bees and honey sources

The two major elements of bees include three bee colonies: hired bees, follower bees, and scout bees, while the honey source is a feasible solution that needs to be solved. The algorithm first associates hired bees with randomly generated honey sources, then each hired bee moves to a new honey source near its current associated honey source, and finally iterates

Evaluate the honey source during the generation process. After hiring bees to complete this process, they share honey source information with the following bees and choose a satisfactory honey source to follow. Reconnaissance bees search for new honey sources according to certain rules. The above process is repeated until the stopping criteria are met.

The standard artificial bee colony algorithm is an optimization method for handling continuous function problems, while the scheduling problem in flexible job shops is a discrete problem of resource allocation, so it is necessary to encode the job scheduling problem to replace the original form.

The quality of the initial population will affect the overall convergence speed of the algorithm. If the initial population is obtained entirely using random methods, the randomness of the initial solution will be too strong; If strategy selection is completely adopted, the initial solution cannot achieve good dispersion, and the quality of the initial solution is difficult to ensure. This will inevitably affect the ability to search for the optimal predicted solution, leading to the need to obtain the optimal solution at the cost of increasing the number of iterations and population size, thereby increasing optimization costs. Therefore, generating a high-quality initial population is a key step in this algorithm. Therefore, this article has designed corresponding initialization rules for the process string and machine string respectively.

Based on the objective function to be optimized in this article, an improved IM operation for the hiring stage in traditional artificial bee colonies is proposed. The process sorting string is subjected to Multi parent Crossover (MX) operation, which does not produce infeasible solutions and can also inherit excellent genes from the parents to the offspring.

In traditional artificial bee colony algorithms, the following bees use a random search method, which does not guarantee that a better honey source will be obtained after the search. Therefore, this article proposes an adaptive variable neighborhood search method, which is an algorithm that adaptively selects neighborhoods with high search efficiency during the search process. This ensures the algorithm’s development towards better honey sources and enhances its local search ability. This article designs two different neighborhood structures.

In traditional artificial bee colony algorithms, if a honey source x_i is not updated after being collected multiple times by the hired bee, that is, after reaching the single search threshold Vlimit, the quality of honey source x_i does not improve, then the current honey source is abandoned, and the hired bee or the following bee transforms into a reconnaissance bee, entering the reconnaissance bee stage. Therefore, the solution process of the bee colony algorithm in this article is as follows:

Step 1: Encoding, which converts the multi-objective and multi constraint problems in 4.2 into single objective problems, while setting optimization weighting coefficients for each component. After encoding conversion, a single optimization objective is obtained:

$$\min F = w_1 T_z + w_2 C_z . \tag{16}$$

Step 2: Set the initial bee colony, establish external files for the bee colony, and initialize the bee colony and external files Set the cutting speed, feed rate, and turning depth for CNC turning, and randomly generate 500 bee individuals within a certain range to form a bee colony.

Step 3: Introduce the Pareto dominance principle and update the external file information of the bee colony;

Step 4: Use neighborhood search strategy to search for individual bees in external files, sort them through Pareto dominance, retain the optimal solution for each individual, and update the external files again;

Step 5: Calculate the following probability of bees during the optimization process, search for the optimal solution, randomly select a more suitable solution, search within the neighborhood range, find the optimal solution, and synchronize the optimal solution to an external file;

Step 6: Set the maximum value and number of iterations for external files, with a maximum number of iterations set to 1000;

Step 7: Utilize the crowding distance between bee colonies to prune them, iteratively obtain the optimal solution, and obtain a set of non dominated individuals. The algorithm process is shown in Fig. 8.

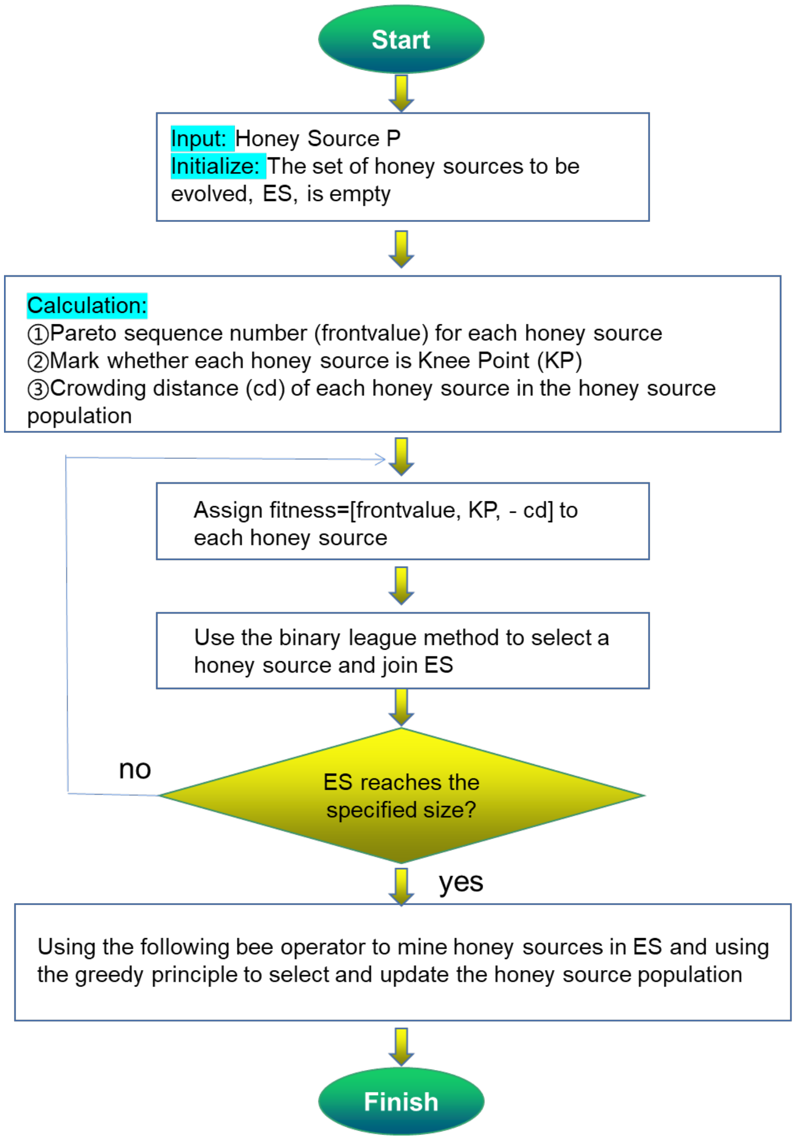

Fig. 8. Bee colony algorithm flowchart

In the improved algorithm, a strategy of random and rule selection is used to initialize the population, which increases the diversity of the population, balances the number of machine runs and energy consumption at the same time, and also avoids relying too much on rules to cause premature algorithm convergence. Adopting a multi parent crossover method during the hiring bee phase to accelerate the search speed of the entire algorithm and enhance the diversity of the population; In the following bee stage, utilizing the honey source information provided by the hired bee, an adaptive neighborhood search method is adopted to effectively search for the global optimal solution near the optimal solution, thereby preventing the loss of the optimal solution.

5 Process Parameter Optimization Process

Selecting the CK7530-800 CNC machine tool produced by Baoji Machine Tool as an example for analysis, the spindle box of the machine tool adopts a combination arrangement of large diameter precision angular contact thrust ball bearings and double row cylindrical roller bearings. The spindle starts quickly and smoothly, with excellent stiffness and large torque at low speeds. Through careful assembly, dynamic balance correction, and running in testing, the spindle achieves the most ideal accuracy, with the characteristics of low temperature rise, small thermal deformation, and high accuracy. It maintains the relative stability of the spindle axis during long-term operation. The spindle speed range is $2500r/\min$; Using open-loop control as the machine tool control method, the number of machine tools is 12, the maximum rotation diameter is 670 millimeters, the minimum motor speed and main motor power of the machine tool are $25r/\min$ and $22kW$, respectively, and the torque and cutting force are $1600kN \cdot mm$ and $6200N$.

The processing object is the most common 45 # steel. During the experiment, it is required to process the experimental material into a stepped axis. The drawing of the stepped axis is shown in Fig. 9. Due to the relatively small diameter of the workpiece being processed, the cutting speed and feed rate are reduced. Taking into account factors such as the material of the workpiece, the material of the turning tool, mechanical properties, and related turning quantities, the initial parameters are set as shown in Table 1.

Table 1. CNC turning process parameters

	Turning speed	Feed rate	Turning depth
Level 1	$120m/\min$	$150mm/\min$	$0.3mm$
Level 2	$160m/\min$	$160mm/\min$	$0.5mm$
Level 3	$200m/\min$	$170mm/\min$	$0.8mm$
Level 4	$250m/\min$	$180mm/\min$	$1.1mm$

Using the bee colony algorithm to optimize the cutting parameters in Table 1, the optimization results are shown in Table 2.

Table 2. Optimization results

Frequency	Turning speed	Feed rate	Turning depth
1	$+2.5m/\min$	$+1.0mm/\min$	$+0.1mm$
2	$+2.7m/\min$	$+1.2mm/\min$	$+0.15mm/\min$
3	$+3.2m/\min$	$+1.3mm/\min$	$+1.2mm/\min$
4	$+2.6m/\min$	$+0.8mm/\min$	$0.02mm$
5	$+2.2m/\min$	$-0.2mm/\min$	$0mm$
6	$+1.8m/\min$	$+0.3mm/\min$	$+0.1mm$

To further demonstrate the effectiveness of the method described in this article, a comparison was made between the processing time and cost of the method used in this article and the pre optimized method at different turning speeds. The processing time was represented by processing efficiency, as shown in Fig. 9.

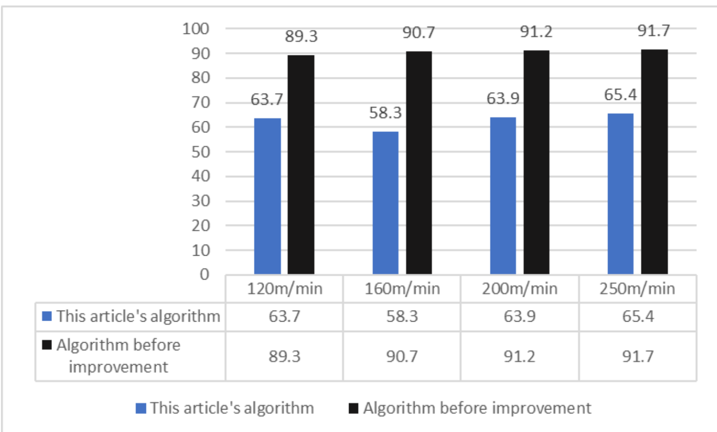

Fig. 9. Comparison of cost results

After comparison, it can be seen that under different turning speeds, the efficiency of CNC turning before optimization is less than 90%, and after optimization, the processing efficiency reaches over 95%. Therefore, under the same task, the processing time can be reduced. From the perspective of processing costs, at different processing speeds, the highest processing cost can be saved by 32.4 yuan, and the lowest can be saved by 26.3 yuan.

6 Conclusion

This article mainly discusses the optimization methods of machining parameters for CNC machine tools. Firstly, the three-dimensional modeling and motion simulation of twin machine tools are implemented, and a data-driven cutting process model is constructed. Then, in the actual production process, in addition to ensuring the normal processing of physical equipment such as CNC machines, data perception during the processing is also completed. Finally, based on the collected data, an objective function that needs to be optimized was established in the optimization process of CNC machining parameters, and the total processing time and processing cost were taken as the optimization objectives. The bee colony algorithm was used to solve the optimization objective function. After experimental simulation, the obtained optimization parameters were found to be able to improve time and processing cost, and the optimization results met the design expectations. Undoubtedly, there are still shortcomings in this article and it is also a future research direction. Firstly, the data collected from digital twin data is not detailed enough, and the amount of data needs to be improved. At the same time, the labels in the data are not clear enough. At the same time, the bee colony algorithm used needs to be improved in avoiding local optima and solving speed.

This article focuses on the dynamic optimization of cutting parameters in CNC machining and proposes a cutting parameter optimization method based on digital twins, which has achieved certain results. However, CNC machining is a dynamic and complex process. This article has preliminarily realized the application of digital twin technology to cutting parameter optimization problems. In future research, the following content needs to be improved:

1) Big data, as the driving source of digital twin, is the foundation and prerequisite for achieving comprehensive mapping of physical space and digital space. Its perception method will have a great impact on the virtual real interaction and synchronous evolution of digital twin. Therefore, how to achieve intelligent perception of industrial field big data is a future research direction.

2) By utilizing multi-sensor fusion technology, various process information in machining can be sensed, ensuring comprehensive monitoring of CNC machining status. Therefore, how to drive the dynamic evolution of twin models through data fusion and intelligent algorithms to improve the accuracy of cutting parameter optimization is an important task in the future.

3) Digital twin technology is a holographic mapping of the physical processing environment, establishing a twin machine tool model with multiple scales and physical fields. It can accurately display the production process of the actual processing environment and perform dynamic simulation optimization. Subsequently, 3D visualization technology and professional simulation software can be used for joint development to build a more realistic twin machine tool model.

4) To build a more comprehensive digital twin model and accurately infer the performance trend of the feed system during the machining process, further exploration is needed in the fusion of multiple models. By combining more models from different fields, a more comprehensive digital twin model can be constructed to comprehensively and accurately predict the remaining service life of the worktable feed system for predictive maintenance. At the same time, the prediction of tool wear and service life caused by feed rate is also an important research content.

5) Multi type sensor data fusion. Currently, edge computing is also an important content in the development direction of the sensor field. In order to more comprehensively understand the operation status of the feed system in processing, you can install multiple types of sensors to obtain diverse and complementary perceptual information. Then, by fusing data from multiple types of sensors, more comprehensive status information of the worktable feed system is obtained. In terms of life prediction and machining process arrangement, cloud computing is used to improve the prediction accuracy and speed of feed system faults during machining. Therefore, in order to better utilize sensor information for fault prediction, we need to further study methods and technologies for data fusion of multiple types of sensors, and study technologies such as edge cloud collaborative computing to achieve optimal fault diagnosis results.

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