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APPLICATION OF FUZZY HESITATION MODEL IN THE OPTIMISATION OF MECHANICAL PROCESS PARAMETERS

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Abstract

In recent years, with the rise of Industry 4.0 and intelligent manufacturing, the optimisation of mechanical process parameters has become a hot issue in the industry and academia. Therefore, the application and value of fuzzy hesitation model in the optimisation of mechanical process parameters are discussed in this paper. First, the relevant data are collected, preprocessed and analysed, and then a preliminary model is constructed for prediction. Based on the verification results of the preliminary model, several strategies are proposed to improve and optimise the model. To improve the efficiency and quality of machining, a series of optimisation strategies for practical applications are also proposed. Overall, this study provides an effective method for the optimisation of mechanical process parameters, and lays a solid foundation for future research and application.

Key Words

Fuzzy hesitation model, mechanical technology, parameter optimisation, apply optimisation strategy in practice

1. Introduction

In today's society, especially in the field of machining, the rapid development of technology makes efficient, accurate and stable operation, and decision-making essential. Faced with uncertain factors and challenges, fuzzy hesitation model comes into being as a more complex, fine and intelligent method. It combines fuzzy logic and hesitation set to deal with uncertain or contradictory information, and has been widely used in many fields, such as medical treatment, finance, and energy. In the field of machining, the model effectively deals with uncertainties in the production process, helps decision makers optimise process parameters and ensure product quality.

With the improvement of global economic integration and production automation, the optimisation and decision-making of mechanical process have a significant impact on the competitiveness, product quality, and production efficiency of enterprises, which makes fuzzy hesitation model become a hot research topic in this field. Kechagias *et al.* [1] found that specific parameter settings significantly improved the manufacturing quality of FFF-TPU. Burcea *et al.* [2] explored the impact of electrical and mechanical design on the robustness of MEMS-ics. Retolaza *et al.* [3] studied the mechanical properties of PPS materials and optimised the FDM processing parameters. Hosseini and Sedighi [4] focused on the influence of friction-assisted extubation on material properties. Zhang *et al.* [5] studied the arc additive manufacturing process of AlCu6Mn welding wire. Liu *et al.* [6] studied the influence of process parameters on mechanical properties of additive manufacturing SMP structures based on FDM. Kam *et al.* [7] applied Taguchi method to optimise melt deposition model parameters and improve the performance of PLA+ filament material. Wafaie *et al.* [8] optimised FFF process parameters to improve the mechanical properties of 3D printed PLA products. Sheikh and Behdinan [9] studied the influence of process parameters on the mechanical properties of components manufactured by additive layered multi-scale models. These studies highlight the importance of the practical application of model prediction and open up new directions for the optimisation of mechanical process parameters. In recent years, the application of fuzzy logic system in the optimisation of mechanical process parameters is increasing, especially in combination with meta-heuristic algorithm, which brings remarkable progress to improve the accuracy and adaptability of the optimisation process. For example, Bacciaglia *et al.* [10] showed how to apply these algorithms to complex mechanical design problems by using meta-heuristic algorithms to optimise controllable propellers. Similarly, the "Bedbug" meta-heuristic algorithm proposed by Rezvani *et al.* [11] shows new ideas and possibilities in solving optimisation problems. Boazzo *et al.* [12] proposed a general design approach for multipole SPM machines for direct drive applications, highlighting the need for precise parameter tuning during the design process and

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demonstrating the direct impact of technological advances on improving mechanical properties. This echoes the work of Mondal and Mhanta [13] who developed an adaptive integrated high-order sliding mode controller for uncertain systems, highlighting an efficient way to deal with uncertainty in mechanical system design and optimisation. These studies show that the performance and reliability of mechanical systems can be significantly improved through precise and advanced control strategies.

In addition, Shyamsundar *et al.* [14] demonstrated the application potential of fuzzy logic in the control of complex systems, especially when using DC servo motors, by adopting the LQR fuzzy logic-based steering gear control system. This study not only supports the application of fuzzy logic in control systems but also implies its potential value in optimising mechanical process parameters.

The work of Nasser *et al.* [15] further expanded the application scope of fuzzy logic by developing an intelligent fault detection and identification method based on fuzzy logic classifiers, providing evidence for the practicability of fuzzy logic in the maintenance and optimisation of mechanical and electronic systems.

These studies are significantly different from the application of the fuzzy hesitation model in the optimisation of mechanical process parameters proposed in this paper. The above research focuses on specific types of meta-heuristic algorithms, while this study focuses on the application of fuzzy logic to deal with uncertainty and fuzziness in process parameter optimisation. In addition, the fuzzy hesitation model combined with meta-heuristic algorithms (such as genetic algorithm and particle swarm optimisation) can deal with fuzzy data and fuzzy rules more effectively, and improve the flexibility and adaptability of decision-making process. The advantage of the fuzzy hesitation model proposed in this study is that it can deal with the uncertainty and hesitation in the mechanical process parameters more accurately. This method not only improves the precision of parameter optimisation but also enhances the adaptability of the algorithm to the change of complex process conditions. This is an important advance in the field of mechanical process parameter optimisation, as it provides a more efficient way to deal with complex decision problems under real process conditions.

The purpose of this study is to discuss the application and optimisation of fuzzy hesitation model in the field of mechanical technology, and to provide accurate and practical decision support in the field of mechanical processing. This study combines the fuzzy hesitation model with the optimisation of mechanical process parameters to improve the efficiency and accuracy of decision making and overcome the limitations of traditional methods in dealing with complex uncertainties. In addition, the innovation of this study is to promote the in-depth research and application of fuzzy logic and decision optimisation methods in machining and other fields, providing a powerful decision-making tool for machining practitioners.

The model of this study is not only innovative in theory but also has important value in practical application. The application of fuzzy hesitation model in the optimisation of mechanical process parameters can effectively deal with various uncertain factors in the production process, such as the change of material characteristics and the fluctuation of equipment conditions. This method makes the machining process more flexible and precise, thereby improving product quality, reducing waste, and optimising production efficiency. Especially in high-precision machining and complex parts production, the application of this model can bring significant economic benefits.

The research document is organised as follows: In the first part, the introduction introduces the research background and the importance of fuzzy hesitation model in the optimisation of mechanical process parameters. In the second part, the theoretical basis of fuzzy hesitation model and its application in different fields are deeply discussed, which lays a foundation for understanding the working principle and application scope of the model. The third part describes the specific application of the model in the optimisation of mechanical process parameters, including the selection of data source, collection, preprocessing, model construction, and parameter setting. In the fourth part, the model is tested and the results are analysed by appropriate verification methods, and the advantages and limitations of the model are discussed. In the fifth part, based on the analysis results, improvement strategies and future research directions are proposed to enhance the practicability and accuracy of the model. On the whole, this paper systematically demonstrates the application of fuzzy hesitation model in the optimisation of mechanical process parameters from theory to practice.

2. Theory and Application of Fuzzy Hesitation Model

2.1 Basic Concept of Fuzzy Hesitation Model

Fuzzy hesitation model combines fuzzy logic and hesitation set to effectively deal with problems containing uncertain, fuzzy or contradictory information [16]. This model transcends traditional binary logic and allows objects to exist in multiple states, providing theoretical basis and new perspective for complex decision making. Fuzzy logic deals with fuzzy phenomena, while hesitancy sets focus on uncertainty in decision making, jointly promoting comprehensive analysis and solution of complex problems [17], [18].

The application of fuzzy hesitation model in many fields proves its practicability and benefit. Assisting in diagnosis and treatment in the medical field, helping doctors process complex medical data. The financial sector deals with risk assessment and investment decisions, while the energy sector optimises energy distribution, especially in terms of efficiency and reliability in renewable energy sources.

2.2 Overview of the Application of Fuzzy Hesitation Model in Other Fields

Because of its unique ability to deal with uncertainty and fuzzy information, fuzzy hesitation model has been widely used in many fields, and its practicality and adaptability have been verified [19]–[22].

In the field of medical applications, fuzzy hesitation models are used in the medical field to aid diagnosis and disease prediction. For example, one study used a fuzzy hesitation model to integrate different medical images and patient data to improve the accuracy of early diagnosis of lung cancer. This method can better deal with the uncertainty and fuzzy information in the diagnosis process and assist doctors to make more accurate decisions.

In the financial field, fuzzy hesitation model is used in risk assessment and investment decision. For example, one study applied fuzzy hesitation models to analyse and predict stock market dynamics to help investors assess potential stock risks and returns. Through the comprehensive analysis of fuzzy information, investors can better understand the uncertainty of market trends and corporate performance.

In the field of energy applications, especially in the planning and management of renewable energy, fuzzy hesitation models evaluate site selection, power generation, cost-effectiveness, and environmental impact. For example, one study used a fuzzy hesitation model to evaluate different wind power generation sites, taking into account geographic location, wind resources, costs, and environmental impacts to provide comprehensive analysis and recommendations for decision makers.

To sum up, the fuzzy hesitation model has shown its practicality and effectiveness in many fields, such as medicine, finance, and energy. These specific application cases not only verify the wide applicability of fuzzy hesitation model but also provide valuable experience and enlightenment for its application in the field of mechanical process parameter optimisation.

2.3 Parameter Challenges and Optimisation Requirements in Mechanical Processes

Mechanical process is a key link in modern manufacturing industry, involving numerous parameters and variables, and its subtle changes have a significant impact on product quality [23]. In the context of global competition, the decision-making and optimisation of mechanical processes are crucial to improving production efficiency and product performance [24], [25].

In machining, the interaction of process parameters, such as cutting speed, feed speed, and tool Angle makes the determination of optimal conditions complicated. Global supply chains and unquantifiable factors, such as operator experience and machine aging add to the difficulty of decision making [26], [27].

Studies have shown that the adoption of advanced technologies, such as fuzzy logic, artificial intelligence, and machine learning can significantly improve the accuracy and efficiency of the optimisation of mechanical process parameters, and help to better deal with fuzzy and uncertain information and predict and optimise process parameters [28], [29]. Fuzzy hesitation model comes into being, which provides a decision support tool integrating quantified and non-quantified information for multi-objective optimisation.

3. Data Collection and Preliminary Processing

3.1 Data Sources and Collection Methods

The study collected data from the following main sources:

Machining centre: Processing equipment, including cutting parameters, machine tool state, processing time, *etc.*

Operator feedback: Collect feedback through interviews, questionnaires, *etc.*

Quality inspection department: Product quality data, dimensional tolerances, surface roughness, *etc.*

Supply chain information: Suppliers, material nature, origin, *etc.*

Table 1 shows the data collection situation.

3.2 Data Preprocessing and Preliminary Analysis

Data preprocessing is a key step in data analysis to ensure that the data used in this study is accurate, complete, and unbiased.

(1) Data preprocessing process: Data cleaning, data conversion, data normalisation.

The data preprocessing situation is shown in Table 2.

(2) Preliminary analysis: Descriptive statistics, correlation analysis, trend analysis.

Through the above preprocessing and preliminary analysis, a clear and standardised data set is obtained.

3.3 Data Characteristics and Impact Factors

To better understand the data and provide appropriate inputs to the model, research needs to dig deeper into the characteristics of the data and the factors that influence it.

(1) Data characteristics:

Time dependent: Certain parameters, such as the temperature of the machine, may fluctuate or trend over time.

Nonlinear relationship: The relationship between some parameters may be nonlinear, such as cutting speed and tool wear.

High-dimensional interaction: Multiple parameters may interact, and they may have different effects on the output when combined than when used separately.

Table 3 shows the data characteristics.

(2) Analysis of influencing factors:

Cutting speed: Mainly affected by material hardness and tool material.

Machine temperature: Related to cutting speed and machine load.

Operator feedback: May be affected by human error and machine condition.

Dimensional tolerance: Affected by tool accuracy and material uniformity.

These data characteristics and impact factors provide insights into the relationship between various variables in mechanical processes and help research to make more

Table 1
Data Collection Information

Data type	Data source	Acquisition method
Cutting parameter	Machining centre	Download directly from the machine monitoring system
Machine state	Machining centre	Real-time monitoring using sensors
Operator feedback	operator	Interviews and questionnaires
Product quality	Quality inspection department	Use measuring tools and equipment for inspection
Material information	Supply chain information, suppliers	Obtained from the data and certificates provided by the supplier

Table 2
Data Preprocessing

Data type	Raw data range	Missing value processing	Data conversion	Post-normalised range
Cutting speed	50–200 m/min	Fill mean	No conversion required	0–1
Machine temperature	20–60°C	Fill median	No conversion required	0–1
Operator feedback	Text description	NA	Text analysis score conversion	0–1
Dimensional tolerance	±0.05 mm	Zero padding	Convert to absolute deviation	0–1
Material type	Such as: Aluminum, steel	NA	One-hot coding	NA

Table 3
Data Characteristics

Data type	Main characteristics	Key impact factor
Cutting speed	High frequency fluctuation	Material hardness, tool material
Machine temperature	Time series upward trend	Cutting speed, machine load
Operator feedback	Unstructured text	Human error, machine state
Dimensional tolerance	Highly sensitive, small range fluctuation	Tool accuracy, material uniformity
Material type	Discrete classification	NA

reasonable assumptions and choices in the model building phase.

4. Construction of Fuzzy Hesitation Model

4.1 Define Parameters and Variables of the Model

The main goal of this study is to optimise various parameters to obtain the best machining results.

(1) Input parameters:

Cutting speed (v): Indicates the speed of processing, selected because it directly affects the processing time and the quality of the finished product, usually expressed in m/min.

Machine temperature (T): The real-time temperature of the machine during processing, important because the temperature change will affect the machine performance and processing accuracy, usually expressed in °C.

Operator feedback score (F): A score based on text analysis that reflects operator satisfaction and feedback with the process, on a scale of 0 to 1.

Dimensional tolerance deviation (D): Indicates the difference between the actual size and the expected size of the machined part, which is directly related to the product quality and is usually expressed in mm.

(2) Output variables:

Processing effect score (S): The processing effect score obtained by synthesising the above parameters ranges from 0 to 1, indicating the overall effect of processing.

Table 4 shows the information of parameters and variables.

Based on the above parameters and variables, a model can be constructed, as shown in the following (1):

$$S = f(v, T, F, D) \tag{1}$$

Table 4
Parameters and Variables of the Model

Symbol	Description	Unit/range
v	Cutting speed	m/min
T	Machine temperature	°C
F	Operator feedback score	0–1
D	Dimensional tolerance deviation	mm
S	Machining effect score	0–1

Where, f is a function representing the influence of the above input parameters on the processing effect score S. This function requires further definition, usually based on historical data and expert knowledge to determine its specific form. Fuzzy hesitation model will help research to define and optimise this function to ensure the best machining results.

4.2 Constraint Setting of the Model

In the actual operation of mechanical processes, various parameters cannot be arbitrarily changed, but are limited by a series of physical, economic or safety constraints.

According to the defined parameters and variables, the constraints are as follows:

(1) Cutting speed (v): Due to the physical limitations of the machine and the durability of the tool, the cutting speed cannot be too low or too high: $v_{\min} \leq v \leq v_{\max}$.
Where $v_{\min}$ and $v_{\max}$ are the minimum and maximum allowable values of the cutting speed, respectively.

(2) Machine temperature (T): To ensure the normal operation of the machine and the quality of the product, the temperature of the machine cannot exceed a certain threshold: $T \leq T_{\max}$.
Where $T_{\max}$ is the maximum allowable temperature of the machine.

(3) Operator feedback score (F): Although this is a subjective assessment, if the score is below a certain threshold, it may indicate that there is a serious processing problem. As the following is shown: $F \geq F_{\min}$.
Where $F_{\min}$ is the minimum acceptable value for the operator feedback score.

(4) Dimensional tolerance deviation (D): To ensure the quality of the product, the dimensional tolerance deviation can not exceed the specified range: $|D| \leq D_{\max}$.
Where $D_{\max}$ is the maximum allowable deviation of the dimensional tolerance.

Based on constraints, the model should not only optimise the machining effect score S but also ensure that all parameters are within the allowable range. This brings additional challenges to the construction and optimisation of the model, but also guarantees its feasibility and effectiveness in practical applications.

5. Model Verification and Result Analysis

5.1 Selection of Verification Method

Validation is a key step to ensure the reliability and practicality of the model.

Verification method:

(1) Cross-validation: This is a commonly used method for model validation, especially when the amount of data is limited. Cross-validation improves the generalisation of the model by constantly re-segmenting the data set to ensure that every data point has a chance to be used as validation. The following (2) is shown:

$$S_{\text{predicted}} = f(v, T, F, D)_{\text{train}} \tag{2}$$

Where f_{train} is the model trained on the training data set.

(2) Bootstrapping: This is a method that generates multiple samples by randomly sampling from the original data set, and then uses these samples for model validation. The bootstrapping method is particularly useful for estimating model accuracy and stability because it allows for repeated sampling, which can provide a more complete understanding of model performance.

(3) Sensitivity analysis: This is a method to examine the response of the model output to changes in the input parameters. Sensitivity analysis helps to identify which input parameters have a significant impact on the model output, thereby guiding further adjustment and optimisation of the model. For example, the study can change the cutting speed v and then observe the change in the machining effect score S, $\frac{\delta \mathrm{S}}{\delta \mathrm{v}}$.

(4) Compare actual and predicted data: The results are predicted by the model and compared with the actual data collected. This is a direct way to check the accuracy of the model and visually show how the model will perform in real-world applications. The following (3) is shown:

$$\Delta S = S_{\text{actual}} - S_{\text{predicted}} \tag{3}$$

Where, S_{actual} is the actual processing effect score, and $S_{\text{predicted}}$ is the predicted value of the model.

To ensure the robustness and wide applicability of the model, multiple validation methods may be selected and used in combination. In addition, based on the results of validation, the model can be further adjusted and optimised to make it more accurate and reliable.

5.2 Comparison Between Model Predictions and Actual Data

To verify the accuracy of the model, the research needs to compare the prediction results of the model with the actual processing effect score. As shown in Fig. 1.

From the figure above, you can see the difference between the model's predicted score $S_{\text{predicted}}$ and the actual score S_{actual}. For example, for data number 1, the model predicted a score of 0.85, but the actual score was 0.87, indicating that the model slightly underestimated the

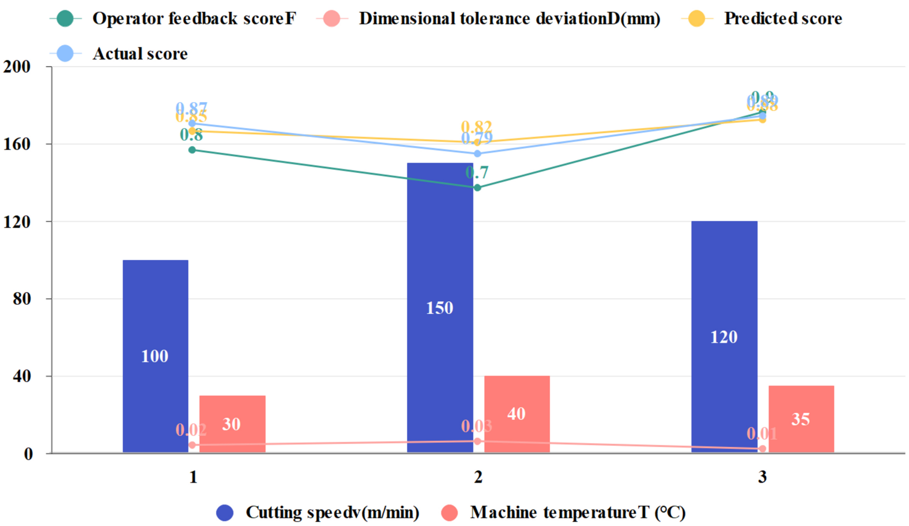

Figure 1. Model prediction and sample data.

processing effect. On the contrary, for data number 2, the predicted score of the model is 0.82, while the actual score is 0.79, which indicates that the model slightly overestimates the processing effect.

To evaluate the overall accuracy of the model, the mean squared error (MSE) between the predicted and actual values can be calculated, as shown in (4) below:

$$MSE=\frac{1}{n}\sum_{i=1}^{n}\left(S_{\text{predicted },i}-S_{\text{actual },i}\right)^{2} \tag{4}$$

Where n is the amount of data. The smaller the MSE value, the more accurate the prediction of the model.

5.3 In-Depth Analysis of the Results and Advantages and Disadvantages of the Model

The model's predictions were found to be very close to the actual data in some cases and biased in others. For example, consider the relationship between machine temperature T and cutting speed v and the prediction error.

Through in-depth analysis, the model results are obtained, as shown in Fig. 2.

The model shows strong adaptability, flexibility, and interpretability in mechanical processes, but the prediction error increases under high temperature and high speed conditions, and the calculation is complicated and the data volume is large.

6. Model Improvement and Optimisation Strategy

6.1 Model Adjustment Based on Verification Results

It is essential to ensure the accuracy and robustness of the model.

Adjust the strategy:

(1) Introduction of interaction terms: Considering that both cutting speed v and machine temperature T have significant effects on the model's prediction, the study can introduce an interaction term $v \times T$ to better capture the interaction between them. The following (5) is shown:

$$S_{\text{new }}=f(v, T, F, D, v \times T) \tag{5}$$

(2) Parameter reweighting: Adjust the weights of each parameter in the model to reduce the dependence on some sensitive parameters. For example, reduce the weight of cutting speed v and increase the weight of machine temperature T.

(3) The introduction of nonlinear transformations: In some parameter ranges may have nonlinear behaviour, can introduce nonlinear transformations, such as logarithmic, exponential or polynomial transformations.

As shown in Fig. 3, the adjustment of parameter weights is presented.

By adjusting the strategy, the prediction performance of the research model at high temperature and high cutting speed is improved.

In short, model adjustment based on verification results is an iterative and continuous process.

6.2 Optimisation Strategy Proposal

The optimisation strategy of the model and mechanical process is proposed to improve the efficiency, reduce errors, and increase the stability of the model in practical application.

(1) Dynamic adjustment of cutting speed (v): Considering that the model is very sensitive to cutting speed, the research can monitor the machining effect score S in real time and dynamically adjust the cutting speed. The following (6) is shown:

$$v_{\text{adjusted }}=v_{\text{current }}+k \times\left(S_{\text{desired }}-S_{\text{actual }}\right) \tag{6}$$

Where, k is an adjustment factor, S_{desired} is the desired processing effect score, and S_{actual} is the actual predicted value of the model.

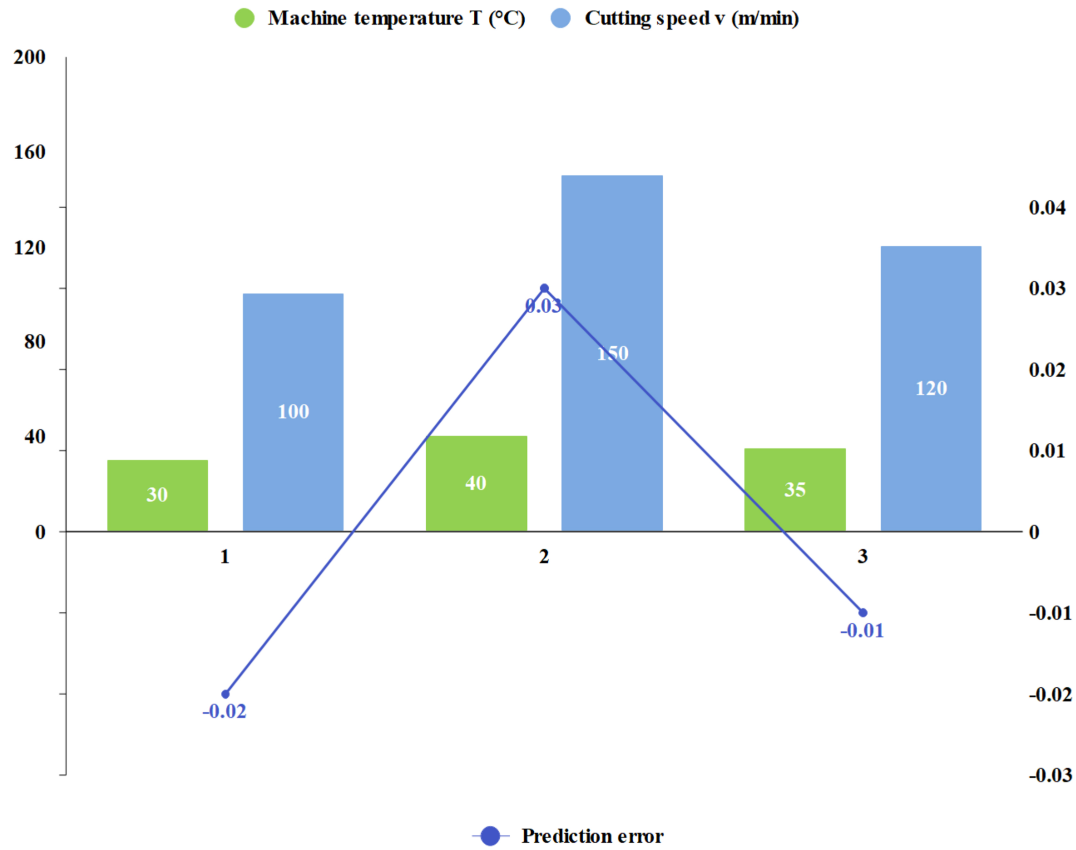

Figure 2. In-depth analysis of the results.

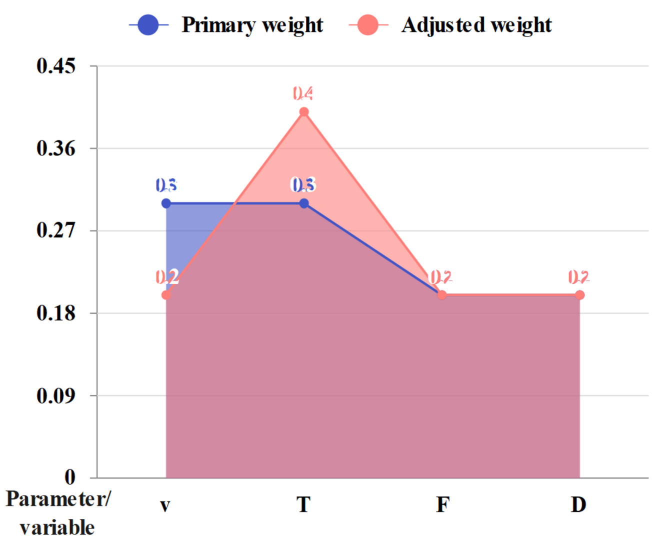

Figure 3. Parameter weight adjustment.

(2) Real-time cooling of the machine: If the temperature of the machine is detected to be close to or exceed its safety threshold, immediately start the cooling system or reduce the speed of the machine.
(3) Adaptive learning: The use of online learning or incremental learning methods allows the model to automatically adjust its parameters and structure based on newly collected data.
(4) Multi-source data fusion: Consider integrating other relevant data (such as the vibration frequency of the machine tool, the wear degree of the tool, *etc.*) to improve the accuracy of the model.

The optimisation strategy is shown in Table 5.

6.3 Verification and Comparison of the Improved Model

After improving the model, it is crucial to verify its performance.

As shown in Fig. 4, the comparison between the predicted results based on the improved model and the actual data is presented.

As can be seen from the above figure, the prediction of the improved model is closer to the actual data at some data points.

Further, according to (4), the MSE of the two models can be calculated for comparison: $\mathrm{MS}E_{\mathrm{old}} = \frac{1}{n}\sum_{i=1}^{n} (S_{\text{predicted, } old \text{ },i} - S_{\text{actual},i})^2$; $\mathrm{MS}E_{\text{new}} = \frac{1}{n}\sum_{i=1}^{n} (S_{\text{predicted, new},i} - S_{\text{actual},i})^2$.

By comparing $\mathrm{MS}E_{\mathrm{old}}$ and $\mathrm{MS}E_{\text{new}}$, you can intuitively see the effect of the model improvement.

7. Conclusion

In this paper, the application of fuzzy hesitation model in the optimisation of mechanical process parameters is discussed. By analysing the available data, we successfully built a preliminary model that can effectively predict the machining effect. However, preliminary verification

Table 5
Optimisation Strategy

Optimisation strategy	Description
Dynamic adjustment of cutting speed	Real-time monitoring and adjustment according to machining results
Real-time machine cooling	Start the cooling system when the machine temperature approaches the threshold
Adaptive learning	Allows the model to be automatically updated based on new data
Multi-source data fusion	Integrate more data sources to enhance the predictive power of the model

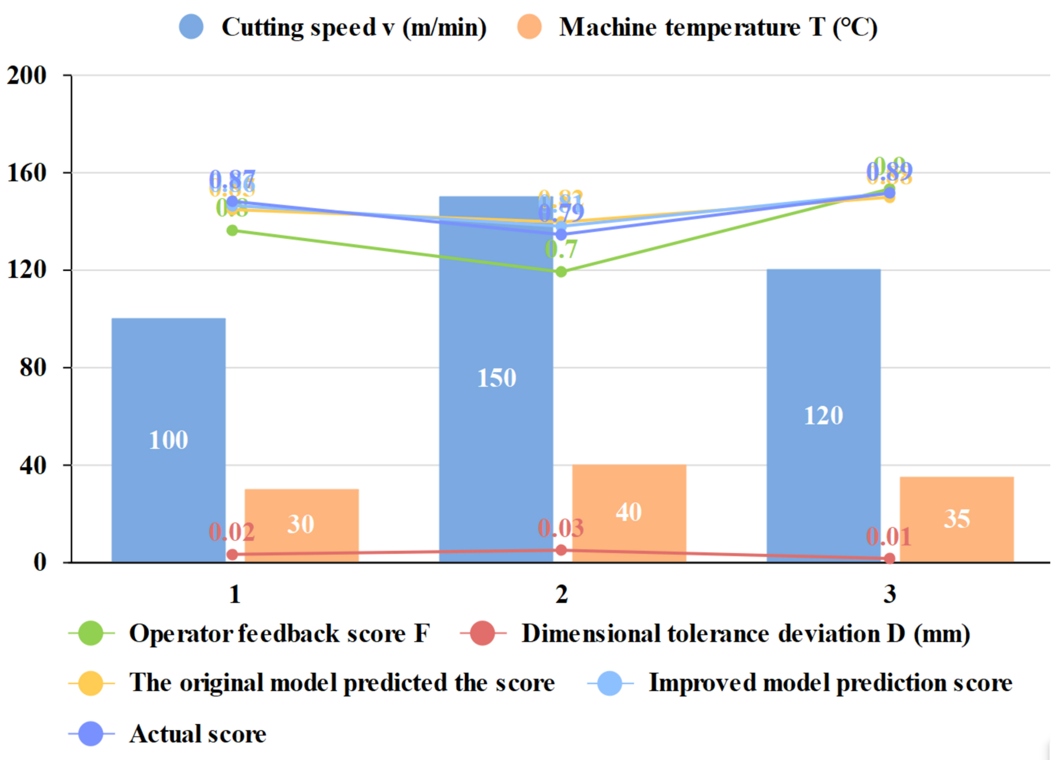

Figure 4. Verification and comparison of the improved model.

shows that the model has prediction errors under certain conditions.

Although the model performs well under standard conditions, it has limited predictive power under extreme conditions and a typical data cases. To improve the prediction accuracy and robustness of the model, we propose a series of improvement strategies, including introducing new interaction terms, reweighting parameters, and applying nonlinear transformations. These improvements significantly improve the adaptability of the model, enabling it to handle complex processing situations more accurately.

The main advantage of the model is that it can combine quantised and non-quantised information to effectively deal with fuzzy and uncertain information in machining. In addition, by introducing advanced algorithms and technologies, the model shows significant potential in improving production efficiency and optimising product quality. However, the limitations of the model are mainly reflected in the need to improve the processing ability of extreme conditions and a typical data, and the current application is mainly concentrated in specific conditions, and the adaptability to a wider range of process parameter changes needs to be further verified.

Given these limitations of the model, the focus of future research should include: further improvement of the model, especially improving its performance under extreme conditions. Explore more efficient algorithms to improve the computational speed and accuracy of the model when processing large-scale data; Test the applicability of the model in different processing environments and expand its application range. These research directions will help to solve the limitations of existing models and further improve their application value and adaptability in practical production.

In summary, this study provides a new set of technical solutions for the optimisation of mechanical process parameters, and provides a valuable reference for technological innovation in the machining industry. Future research will continue to focus on improving the model to make it more accurate, reliable, and applicable to different processing environments.

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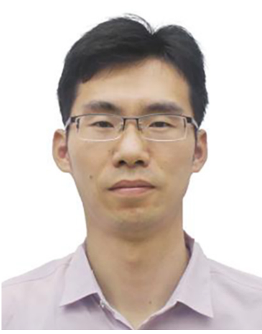

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