

Spindle Power Prediction and Feed Rate Optimization based on Impeller Milling

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ABSTRACT

This study is dedicated to solving the control hysteresis problem caused by the slow response speed of traditional fixed-parameter machining and control systems, and investigates a method aimed at combining deep learning and PID controllers to achieve intelligent optimization of the feed rate for ternary impeller milling. A two-stage step-by-step prediction of the spindle power is used to take advantage of the LSTM prediction optimization solving algorithm's fast response to time series data processing, and the PID controller adjusts the feed multiplication rate by proportional, integral and differential control strategies according to the model output to achieve constant power stable cutting with pre-adjustment of feed multiplication rate for CNC milling process. The experimental results show that the intelligent optimization scheme of feed multiplication for ternary impeller milling based on deep learning and PID controller has high effect. Through continuous learning and intelligent adjustment, the machining efficiency is significantly improved, while the machining quality and stability are ensured.

KEYWORDS

Prediction Algorithm; PID Control; Feed Rate Optimization; Stable Cutting.

1. INTRODUCTION

Milling, as a commonly used machining method in CNC machine tools, has become an indispensable part of the modern manufacturing process by virtue of its wide applicability. Compared with traditional machining, modern CNC milling still consumes a huge amount of energy generated by machining, although the machining face has changed. In order to further optimize the processing efficiency, accurate selection and adjustment of milling parameters is particularly critical. The traditional way of selecting machining process parameters usually relies on the experience of programmers and machining manuals, and often selects conservative feed rate parameters, which leads to low machining efficiency, and even if some offline optimization algorithms are used, it is difficult to effectively adapt to the dynamically changing demands of the machining process. Combining the self-adaptive ability of deep learning and the stability of PID control, a novel intelligent optimization method combining online monitoring and learning is provided. This method not only adjusts the feed rate in the milling process, but also ensures that the energy consumption of the machining process is optimized, which is an important step to improve the intelligent level of CNC milling machining.

Scholars at home and abroad have achieved a series of results for feed rate optimization. Some scholars use offline data to optimize the feed rate. For example, Meijer [1] proposed a simulation method for predicting the actual feed rate in precision micro-milling of hardened high-speed steel and identifying critical machining areas in CNC programs. Dai [2] focused on the cavity milling process

and used historical data to simulate the spindle power and optimize the feed rate accordingly. Zhao [3] investigated the offline optimization method of feed rate for multi-axis milling machining, which was conducted offline, but the method provided theoretical basis and data support for online optimization. In addition, Fu [4] focused on how to optimize the feed rate in complex surface milling based on the cutting force prediction model. Zhao [5] used artificial neural network to optimize the feed rate of three-axis roughing milling in a multi-objective way, and verified experimentally that this method can improve the machining efficiency and the stability of the spindle load. The study of Zhou [6] proposed an optimization method for five-axis roughing feed rate based on spindle power cutting load constraints and feed axis kinematic constraints. Yin [7] used genetic algorithms for selecting the cutting parameters of CNC milling in order to optimize the material removal rate and to reduce the carbon emission and improve the energy efficiency. The study by Yin [8] focused on the optimization of roughing feed rate for three-axis milling based on a spindle power model, aiming to improve milling efficiency and protect equipment by predicting and controlling spindle power. Finally, Akiyama [9] investigated the effects of milling conditions on surface roughness and milling time and found the optimal parameter combinations through offline optimization. In this study, for the complex machining part ternary impeller, the method of combining spindle power prediction and feed speed optimization control is used to predict the time series machining data, and then the optimization results are fed back for regulation and control, which effectively solves the problem that the traditional optimization cannot be accurately optimized in real time by using historical data. Adopting deep learning algorithm, the feed multiplier is defined as the action space of the algorithm, and the PID controller is integrated as an auxiliary optimization tool in order to achieve accurate and dynamic feed speed optimization.

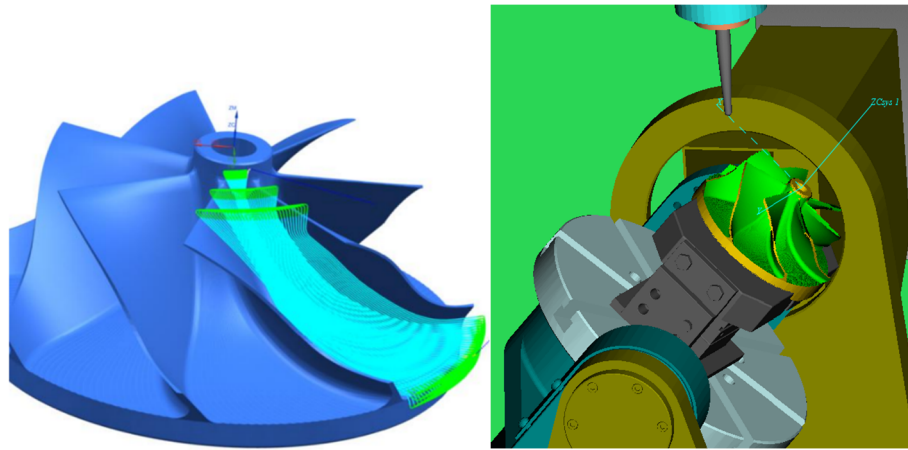
2. PHYSICAL SIMULATION OF IMPELLER PROCESSING

The importance of aluminum alloys in high-end manufacturing such as aerospace cannot be overstated. They are favored not only for their light weight and high strength, but also for their excellent machinability, making these materials ideal for manufacturing complex parts. The machining process for thin-walled aluminum alloy parts, especially those with complex curved surfaces such as impellers, faces many challenges. Traditional milling techniques are often inefficient and underprecise when dealing with such parts, making it difficult to meet the stringent requirements for part accuracy and performance in high-end manufacturing. This not only increases the production cost, but also may affect the final quality of the product and the reliability of the system.

With the continuous advancement of computer-aided design (CAD) and computer-aided manufacturing (CAM) technologies, simulation plays an increasingly critical role in the field of part machining. Simulation allows the prediction and evaluation of various problems that may arise during machining before actual machining, thus optimizing machining parameters and improving machining efficiency and accuracy. In the machining of aluminum alloy thin-walled parts, the application of simulation technology can not only significantly reduce the material removal rate and shorten the machining time, but also ensure that the machined parts have higher precision and better surface quality. The application of this technology is of great significance for improving the machining quality of aluminum alloy parts in high-end manufacturing fields. The complexity of impeller machining requires the use of high-precision and high-efficiency machining methods. The development of an impeller machining method based on simulation technology not only improves machining efficiency and reduces costs, but also enhances product quality and reliability. The development of this machining method has significant practical significance and application prospects for high-end manufacturing fields such as aerospace.

First, a 3D model is created in UG software based on the design parameters of the impeller. Next, the model is optimized to ensure that it meets the performance and manufacturing criteria. After modeling, the impeller model is exported to STL or STEP format for simulation in Vericut software. The

simulation environment is set up in Vericut, including the 5-axis machine and tool parameters, and then the machining program is imported to simulate the machining path of the impeller. During the simulation, check and ensure that the machining path is free from collision or overcutting problems. According to the simulation results, adjust the machining parameters to optimize the machining effect. After confirming that there is no error, the G code of the machining program is output and used for actual machining on the CNC machine. After machining, the impeller is cleaned, deburred and other post-processing, and quality inspection to ensure that the product meets the design requirements. This series of steps constitute a complete process from UG modeling to Vericut simulation of the impeller. As shown in the figure for the impeller processing path planning and physical simulation processing.



(A) Machining path planning

(B) Process Physics Simulation

Figure 1. Impeller Processing Simulation

3. SPINDLE POWER PREDICTION MODELLING

3.1. Exponential Modeling of Machining Parameters and Power

In the process of CNC milling, for the optimisation of cutting parameters of complex curved hard-to-machine workpieces, some electrical data, such as spindle current, spindle power, etc. can be used as a source of data for process optimisation, and the cutting power of milling can, to a certain extent, reflect the size of the tool in the size of the tangential force in the milling process, the tangential force usually occupies a dominant position, so the use of spindle cutting power to reflect the size of the cutting force is reasonable. Therefore, it is reasonable to use spindle cutting power to reflect the size of cutting force. Through the spindle cutting power to guide the selection of cutting parameters, to improve machining efficiency, machining quality, extend tool life and reduce production costs is of great significance. In order to accurately predict the spindle power of the machine tool, a two-stage spindle power prediction method is used, the first stage through orthogonal experiments with multiple linear regression:

After theoretical analysis, it is concluded that most of the machining parameters are selected such as spindle speed, feed rate, depth of cut, width of cut and other machining parameters, so the coefficients of the influence of these process parameters on the spindle power are calculated to find a set of optimal solutions. Derived from the cutting power calculation model:

$$P_c = C_n f_z a_p a_e \quad (1)$$

The transformation into logarithmic form is:

$$\ln(P_c) = \ln C + a \ln n + b \ln f_z + c \ln a_p + d \ln a_e \quad (2)$$

By reviewing the literature, it was found that orthogonal experiments can address the full effect of the four machining parameters on spindle power variations, establishing representative points for efficient experimental design.

3.2. LSTM Prediction Modeling

In the second phase, the Long Short-Term Memory (LSTM) network in machine learning is used to learn the temporal relationships in the sequence data, especially involving changes in the x, y, and z axes. By learning fixed patterns and path sequences in the data, a model is trained that can accurately predict the sites of abnormally high spindle power. The LSTM model performs well with sequential data, capturing areas of high axial variation and making accurate predictions. Before starting the training, the data was first cleaned. The process of data cleaning includes removing blank columns and rows, and dealing with missing values, among other things. Through these steps, the integrity and consistency of the data were ensured to prepare the data for subsequent model training. Next, the dataset is divided into a training set and a test set in order to evaluate the model after training it. In order to eliminate the effect of the magnitude differences between different features on model training, the feature data were normalised. This ensures the validity and stability of the model during the training process.

LSTM model is a neural network model for sequential data. Two LSTM layers are used, where the first layer has 64 units and uses the tanh activation function and L2 regularisation. The second LSTM layer has 32 units and also uses the tanh activation function and L2 regularisation. Between these two LSTM layers, a Dropout layer was added to reduce the risk of overfitting. Finally, two Fully Connected layers were added, the first of which has 64 neurons and a ReLU activation function, and the last layer is an output layer for predicting the spindle power. During the compilation of the model, the Adam optimiser and the mean square error (MSE) were chosen as the loss function. The Mean Absolute Error (MAE) of the model was also calculated to evaluate the performance of the model on the test set. After the training of the model was completed, predictions were made on the test set using the model and the R2 score and Mean Absolute Percentage Error (MAPE) were calculated between the predicted results and the actual values. The R2 score is used as a measure of how well the model fits the data while the MAPE helps to understand the predictive accuracy of the model and plots the actual values versus the predicted values as well as the relative percentage error.

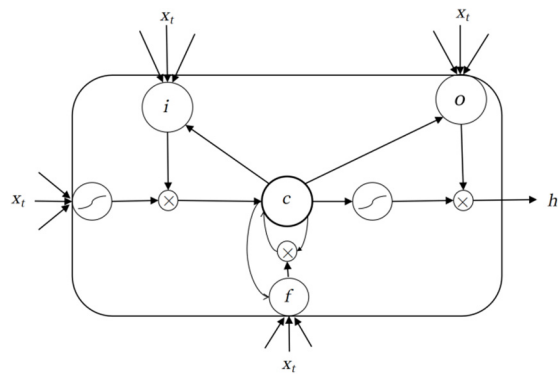


Figure 2. LSTM memory cell

Through the above steps, data with time series nature can be modelled and predicted using the LSTM model, which helps to find out the areas where the spindle power is abnormally high and predict it accurately. The average value of spindle power is set by test cutting to keep the spindle power to maintain a stable cutting condition. The feed rate decreases when the average spindle power value is exceeded, and changing the feed rate helps to protect the tool, reduce tool change time and improve machining efficiency.

4. PID CONTROLLED FEED RATE OPTIMISATION

In this paper, by improving the machining spindle power increases, while the feed rate remains unchanged may lead to tool breakage, increase the time of tool change, etc., put forward the "constant power, regulate feed" optimization scheme, in the cutting spindle power is too large place in a timely manner to reduce the feed rate, set the minimum feed speed warning line, and according to the size of the cutting volume adjustment Adaptive machining method of feed speed adjustment according to the size of cutting volume to avoid tool wear and rupture. Through the real-time monitoring of the control system, the processing status of spindle power and feed rate can be observed visually, and the machining time saved can be recorded synchronously, so as to maintain the optimal processing efficiency, give full play to the performance of the tool, improve the processing efficiency, and reduce the power volatility.

The initial selection of machining parameters during milling is always constant, which leads to inefficient machining, whereas online optimisation and feedback provides a way to make real-time adjustment of feed multiplier according to the actual state, such as spindle power changes, in which the precise feedback control mechanism plays a key role. The multiplier will be verified by simulation in the digital twin model, if the simulation response satisfies the constraints then the new feed multiplier will be passed to the PID control system, otherwise, the control parameters will be adjusted and the process will be repeated until a feed multiplier that satisfies the constraints is found.

The task of the PID controller is to ensure that the actual feed rate of the machine can quickly and accurately follow the optimal rate recommended by the deep learning model. It achieves this by adjusting the control parameters proportional, integral and differential. The PID controller responds quickly to the set point of the feed multiplier, narrowing the error through proportional adjustment and eliminating residuals using integral adjustment. This closed-loop feedback allows the latest speed adjustment information to be continuously transferred to the PID, ensuring precision and stability of the machining process and keeping the machine optimal under changing conditions. Through the combination of digital twin and PID controller, the predictive function of the model is brought into play and the real-time control advantages of PID are retained, which ultimately can achieve rapid and optimal control of feed multiplication for the actual milling process.

As machining proceeds, the deep learning model is incrementally trained and updated by collecting data on the working conditions and the corresponding optimal feed rate. The updated model is used to optimise the optimal feed rate and convert it to a feed multiplier. If the predicted optimal speed is 2 m/min and the current nominal feed rate is 1 m/min, then the feed multiplier is calculated to be 2. This multiplier is transmitted to the PID controller in the form of a digital quantity, and the PID receives the new multiplier signal as an input to the control process, and the PID internally calculates a control output based on its own control algorithm, combined with the new multiplier signal, and drives the motion of the feed axis. and drive the motion of the feed axes. Eventually, the actual feed speed of the machine is adjusted according to the output of the PID, realising closed-loop control of the multiplier.

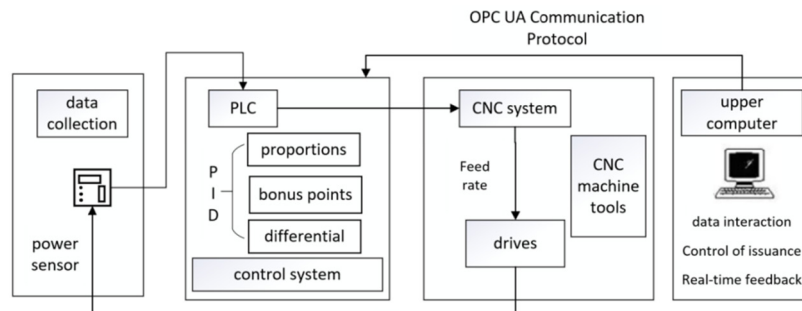


Figure 3. Schematic diagram of control system

Through the synergy of deep learning and PID control, it not only greatly improves the machining accuracy, but also enhances the adaptability and response speed of the system, demonstrating the value of the application of intelligent manufacturing technology.

5. EXPERIMENTAL VERIFICATION

5.1. Orthogonal Experimental Design

In this paper, the cutting power is used as the monitoring variable and the machining parameters are used as the independent variables to design orthogonal experiments, and the basic relational equation between power and machining parameters is used as the first stage model, and the path of impeller cutting is used as the second stage prediction model using the time series prediction algorithm to forecast the future trend of the power change step by step. Then the prediction model is combined with the control logic to improve the response speed and machining efficiency. Firstly by designing three levels of orthogonal experiments as follows:

Table 1. Experimental factors and levels

factors	Spindle speed (r/min)	Feed (mm/min)	Cutting depth (mm)	Cutting width (mm)
1	800	50	0.1	1
2	1000	100	0.2	2
3	1500	150	0.3	3

Design orthogonal experiments as follows:

Table 2. Table of orthogonal experiments

factors	Spindle speed (r/min)	Feed (mm/min)	Cutting depth (mm)	Cutting width (mm)	Spindle power (W)
1	800	50	0.1	1	12.5
2	800	50	0.2	2	18.6
3	800	50	0.3	3	16.8
4	800	100	0.1	2	16.2
5	800	100	0.2	3	19.2
6	800	100	0.3	1	14.1
7	800	150	0.1	3	18.5
8	800	150	0.2	1	16.4
9	800	150	0.3	2	18.4
10	1000	50	0.1	2	20.1
11	1000	50	0.2	3	24.2
12	1000	50	0.3	1	19.2
13	1000	100	0.1	3	23.8
14	1000	100	0.2	1	24.4
15	1000	100	0.3	2	25.6
16	1000	150	0.1	1	23.2
17	1000	150	0.2	2	26.4
18	1000	150	0.3	3	31.2
19	1500	50	0.1	3	34.4
20	1500	50	0.2	1	33.2
21	1500	50	0.3	2	40.8
22	1500	100	0.1	1	39.2
23	1500	100	0.2	2	37.6
24	1500	100	0.3	3	41.8
25	1500	150	0.1	2	42.4
26	1500	150	0.2	3	46.6
27	1500	150	0.3	1	49.9

A multivariate linear model was developed as:

$$P=0.000723n^{1.3966}f_z^{0.1793}a_p^{0.0926}a_c^{0.1287} \quad (3)$$

In the first phase of the study, we constructed a spindle power calculation model based on process parameters, and theoretically deduced the relationship between spindle power and process parameters. Through orthogonal experiments and multiple linear regression, the influence coefficients of each factor on spindle power were found.

5.2. Prediction Algorithm Construction

A predictive model for the second stage of machine learning based on the first stage predictive model. A sequential model containing two layers of LSTM and two layers of Dropout was constructed by using a long short-term memory network to prevent overfitting. L2 regularisation was added to the LSTM layer to further improve the generalisation of the model. The model was compiled using the Adam optimiser and mean square error loss function and trained on the training set for 100 cycles using a batch size of 32 and 20% of the data was retained for validation during training. After the training was completed, the performance of the model was evaluated on the test set, the results of the evaluation were shown in terms of the mean absolute error (MAE) and R2 score of the model, which was evaluated to be 2.51 and the R2 score of the model was 0.9998, and the mean absolute percentage error (MAPE) on the test set was calculated to be 0.9281%, and in order to demonstrate the model prediction effect in a more intuitive way, the test set was selected. In order to show the prediction effect of the model more intuitively, the last 500 data points in the test set were selected to compare the actual values with the predicted values, and the corresponding graphs were drawn.

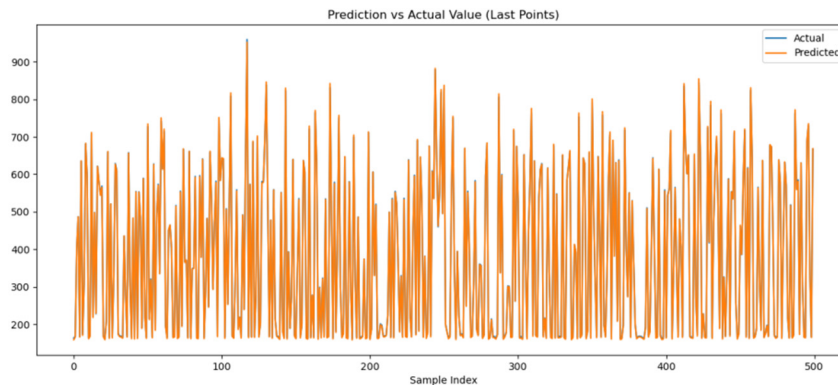


Figure 4. LSTM model prediction results

5.3. Feed Rate Optimization Results

A model for accurately predicting the spindle power of a machine tool is constructed through the above process, and its effectiveness is verified through a series of evaluation criteria. In the control algorithm, a constant power value suitable for the machining path is found through the first trial cutting as a reference value in the power control process, and the power estimation value fused by the prediction model is compared with the target constant power value to calculate the power error, which is inputted into the PID controller for real-time adjusting of the feed multiplication rate.

Optimisation of the process parameters during machining reduces the spindle power fluctuation during machining and protects the tool. Since the milling depth and width cannot be changed during machining, and the feed multiplier can be directly reflected in the G code, it is relatively easy to adjust the feed multiplier. In some positions where the cutting volume is large, the feed multiplier is too high, which may lead to tool breakage or even broken tools, and in some positions where the cutting volume is small, the feed multiplier is too small, which may lead to inefficiency because the

advantages of the spindle motor are not utilised. The optimisation results are shown in the figure below:

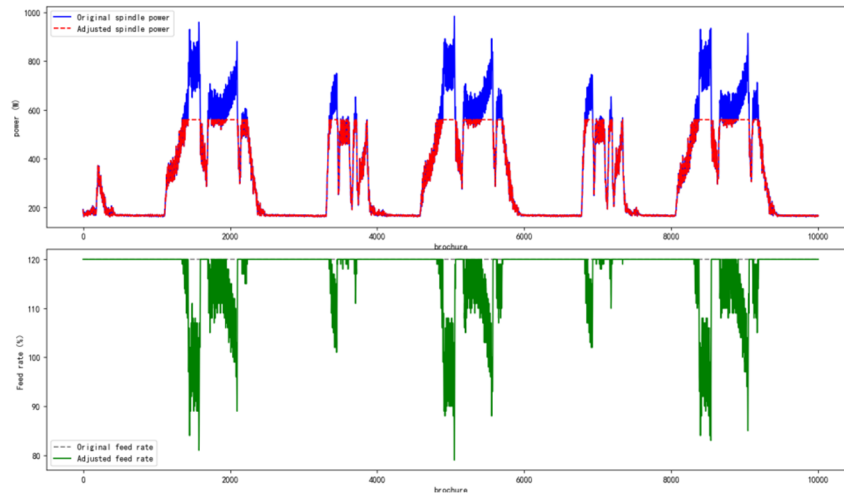


Figure 5. Feed rate optimization results

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