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Application of Neural Network in Machine CAD Processing Parameter Selection

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Abstract. In order to realize the optimization of the comprehensive application efficiency of CNC machine tools and realize the high efficiency and low cost machining, the application of neural network in the selection of machining parameters of mechanical automatic CAD was proposed. With DMC60H NC machine tool as the test platform and shell aluminum alloy parts processing as the research object, the experimental data of NC milling were extracted, and the optimization model of NC milling parameters was established by BP neural network. Through the analysis and research of the experimental data of NC milling parameters, the processing principles of test data and sample data were proposed. The sample data is optimized, the convergence accuracy, convergence speed and prediction accuracy of BP neural network model are improved, and the composition proportion of verified data is analyzed. The test results show that the maximum absolute error of the spindle speed is 13.3%, the minimum absolute error of the spindle speed is 0.19%, and the average absolute error of the spindle speed is 5.51%. The maximum absolute error of feed velocity is 28.21%, the minimum absolute error of feed velocity is 0.39%, and the average absolute error of feed velocity is 3.64%. The maximum absolute error of processing time is 20.10%, the minimum absolute error of processing time is 0.27, and the average absolute error of processing time is 3.89%. The proposed numerical control milling parameter optimization method has strong practicability and certain advanced nature, and can effectively improve the machining efficiency. It is of great significance to realize the optimization of comprehensive application efficiency and high efficiency and low-cost machining of NC machine tools.

Keywords: BP neural network; Milling process; Validation data.
DOI: https://doi.org/10.14733/cadaps.2024.S6.85-94

1 INTRODUCTION

In the milling machine processing planar workpieces, we often see that there is a size error due to the blank, resulting in the milling cutter processing of the back of the cutting tool amount changes, thus causing the radial cutting force and process system displacement of the milling cutter have a certain change. The amount of cutting and cutting force is large, and the phenomenon of the process system is also large, resulting in the displacement of the process system is also large. On the contrary, the amount of cutting is small, the cutting force is small, the phenomenon of the process system is reduced, and the displacement of the process system is small. The final result is that the original error on the blank will be repeatedly reflected on the workpiece to be processed, which is called "error reflection". Under normal circumstances, when the blank error is large, the machining process is divided into several times, which can effectively reduce the machining error caused by the error reflection and improve the machining accuracy.

According to the error replicating theory, the error replicating coefficient reflects the influence of blank error before machining on the workpiece error after machining, and the error replicating coefficient is related to many factors such as the stiffness of the process system, cutting conditions, feed rate and the hardness of workpiece material, and presents a complex nonlinear relationship, which is difficult to calculate accurately through the formula. In the past, in conventional machining, machining parameters were determined prior to machining according to the experience of the machining personnel or by referring to the machining manual. However, in the actual process of machining, the working conditions are constantly changing; the pre-specified machining parameters often cannot get the best machining quality.

In particular, the original error of the blank will be mapped to the workpiece after processing, which makes the processing quality of the workpiece difficult to ensure. Although repeated processing can reduce the error reflection phenomenon, each processing depth selection is different from person to person. For such the same precision requirements of the workpiece, the quality of different people processing is very different. This is not only difficult to ensure the quality of the workpiece processing, but also conducive to the automatic control of the processing process.

An artificial neural network (ANN) is a large-scale parallel distributed processing and nonlinear system composed of many simple processing units (neurons or nodes) designed to exploit the structure and properties of the human brain. It mimics the human brain's information processing, storage, and processing processes to a certain extent and level, so it has intelligent processes such as learning, memory, and computation. A neural network has some amazing properties: it can be anonymous; anyone don't have to have an exact mathematical model; Good at learning useful knowledge from outside ideas/information; Easy to complete during calculation. As a result, data processing methods can solve difficult and intractable problems, especially in thinking (imagination), thinking, and remembering [1-2] as shown in Figure 1:

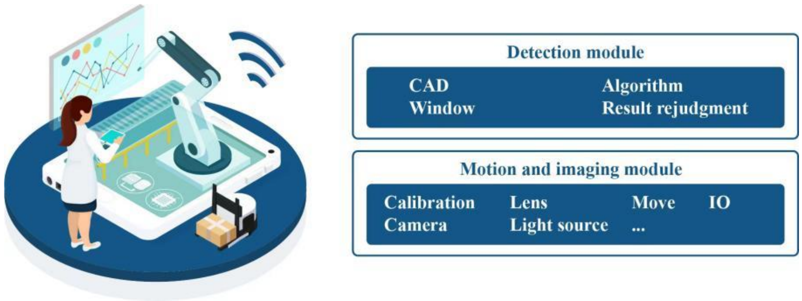

Figure 1: Automatic CAD processing parameters.

2 LITERATURE REVIEW

Due to the early start of industrialization and manufacturing in foreign countries, foreign scholars have done a lot of investigation on processing energy consumption. The energy consumption calculation optimization model is put forward to predict and optimize the energy consumption of the three-axis milling machine. Under the full consideration of the influence of cutting parameters on energy consumption, MATLAB optimization toolbox is used to solve the problem. Some experiments have also been carried out on CNC milling machines, and the prediction accuracy of the energy model is above 90%. An analytical model of cutting specific energy prediction based on cutting parameters in cyclone milling is presented.

In order to verify the correctness of the model, the analytical model was applied to the cyclone milling of ball screw shaft. The results show that the analytical model can predict the specific cutting energy effectively. Many scholars have studied and analyzed the problem of machine tool energy consumption. Based on MTConnect, data acquisition of TC500R vertical machining center was carried out to analyze the energy consumption composition of NC machine tools. According to its energy consumption characteristics, an empirical model based on three cutting factors was established.

The machine energy consumption was predicted by particle swarm optimization support vector machine regression. In the actual processing process, we can not only consider the consumption of processing energy in the production of products, but also consider the tool cost, surface quality and other factors. If the tool is damaged and the surface quality is damaged only for the purpose of energy saving, the gain is not worth the loss. Therefore, the single objective optimization is not in line with the actual processing and production situation, and the multi-objective optimization is the better choice.

Based on a large number of cutting experiments, the energy consumption model of machine tool considering tool wear was obtained, and the tool wear state monitoring was realized. PSO algorithm and grey relational degree analysis were used to optimize the machining parameters of machine tool processing efficiency, workpiece surface quality and machine tool processing energy consumption. It can be seen from the literature that the investigation on multi-objective optimization in the machining process has been very in-depth, most of which is the optimization of energy consumption and surface roughness. However, there are few multi-objective optimization studies on tool wear, energy consumption and surface roughness in micro-milling process [3-5].

In this essay, DMC60H CNC machine tool is used as the test platform, and the processing of shell aluminum alloy parts is used as the research object to extract the numerical control milling processing test data. The optimization model of NC milling parameters is established by BP neural network, and the experimental data of NC CAD machining is processed and studied [6-7].

3 RESEARCH METHOD

3.1 Processing of Test Data

In order to improve the utilization of test data, discrete test data must be processed to comprehensively describe the NC machining process. According to the actual production situation, the test data of surface roughness and dimensional accuracy shall be processed.

3.1.1 Surface roughness

The principle of surface roughness treatment in the test data is to use the first series of surface roughness and treat according to the actual requirements of field measurement and processing, as shown in Table 1.

First series	*0.4*	*0.8*	*1.6*	*3.2*	*6.3*
Measured value	R_a≤0.4	0.4< R_a≤0.8	0.8< R_a≤1.6	1.6< R_a≤3.2	3.2< R_a≤6.3
Processing value	0.4	0.8	1.6	3.2	0.6

Table 1: Surface roughness treatment principles μm.

3.1.2 Dimensional accuracy

According to the test purpose and the requirement of neural network model sample data, the processing principle of dimensional accuracy is based on the standard tolerance table. The dimensional tolerance is converted to the standard tolerance IT, and the value of the standard tolerance IT is taken as the input data of the dimensional accuracy sample [8].

3.1.3 Principles of sample data selection

The quality of sample data directly affects the convergence speed and prediction accuracy of neural network model. Based on the research and analysis of test data processing, combined with the characteristics of CNC milling, the selection principles of sample data are formulated as follows:
(1) Sample data is selected with the size of the surface roughness as the target, that is, under the same conditions of other processing, sample data is selected with higher surface quality.
(2) Sample data is selected with the target of approaching the intermediate tolerance size, that is, test data close to the intermediate tolerance size is taken as sample data.
(3) Select sample data with high processing efficiency as the target, that is, take the test data with the shortest processing time as the sample data.
(4) Sample data were selected by multi-objective optimization under the interaction of surface roughness, intermediate tolerance size and machining efficiency.

3.2 The Establishment of BP Neural Network Model

"Neural Network" or "Artificial Neural Network" (ANN) refers to a nonlinear system composed of a large number of simple computing units (namely neurons), which mimics the information processing, storage and retrieval functions of human brain nervous system to a certain extent and level. Therefore, it has intelligent processing functions such as learning, memory and calculation [9-10].

It has been known since the early 20th century that the human brain works differently from today's computers. Human brain is a highly complex, non-linear and parallel information processing system formed by a large number of basic units (called neurons) through complex interconnections. The human brain is superior to modern computers in many aspects of performance. So it naturally occurred to people to explore new ways of representing, storing and processing information in ways that mimic human intelligence. A new computer processing structure model is realized, and an information processing system closer to human intelligence is constructed to solve the problems that are difficult to solve in the field of practical engineering and scientific research. It will greatly promote the progress of science and bring about great changes in every field of human life.

BP learning algorithm, also known as Error Back propagation algorithm, is a kind of guided learning algorithm used to learn weight and threshold of BP network. Its main principle is that there are P learning sample vectors, and the corresponding expected output is $\mathrm{d}^{(1)}\mathrm{d}^{(2)\cdots}\mathrm{d}^{(\mathrm{p})}$. Learning is through error correction weight, which is $\mathrm{y}^{(\mathrm{p})}$ and close to $\mathrm{d}^{(\mathrm{p})}$. The rule is based on the minimum mean square error criterion. That is, when a sample (let be the pth sample) is input into the network and output is produced, the mean square error shall be the sum of the squared errors of each output unit, i.e., Equation (3.1)

$$E^{(P)} = 1/2\sum_{i=0}^{m-1}\left(d_l^{(p)} - y_l{}^{(p)}\right)^2 \tag{3.1}$$

When all samples are entered once, the total error is equation (3.2)

$$E_A = \sum_{p=1}^{p} E^{(p)} = 1/2\sum_{p=1}^{p}\sum_{i=0}^{m-1}\left(d_l^{(p)} - y_l^{(p)}\right)^2 \tag{3.2}$$

In BP learning algorithm, the learning is divided into two stages: the output of each hidden layer and output layer is calculated backward and forward; Backward propagation from backward forward error is used for weight correction until desired goal is achieved [11-13].

Assume a three-layer BP network with input node x_i and hidden layer node y_j and output node z_l. The weight of the network between the input node and the hidden node w_{ji} The weight of the network between the hidden node and the output node is v_{lj}. When the expected value of the output node is t_1.

In the case of given machining requirements (dimensional accuracy, surface roughness, etc.) and working conditions (machine tool, tool, fixture, etc.), BP neural network is used to build the numerical control machining and milling parameters process model. The optimization of NC milling parameters can be effectively solved through the optimization of test data, sample data and network training.

Taking DMC60H NC machine tool as the research platform and operating system as Siemens840D power line, milling parameters can be selected including spindle speed n and feed speed V_f. Considering the evaluation of milling efficiency, processing time is added, so the output layer neurons are: spindle speed, feed speed and processing time. The cutting tools used in the production are T-milling cutter and cylindrical milling cutter, and the processing process is to remove all the excess material in one cut. Considering that the number of neurons in the input layer is greater than that in the output layer, the input layer neuron is composed of 9 neurons, namely, tool type, tool suspension, tool diameter, tool aperture ratio, basic size, cutting width, cutting depth, dimensional accuracy and surface roughness. It is proved that the feedforward layered neural network with single hidden layer can approximate any continuous function with arbitrary precision. In terms of the selection of the number of hidden layer neurons, the actual operation adjustment method is mainly adopted, that is, the number of hidden layer neurons is constantly adjusted until the convergence accuracy and convergence speed meet the requirements [14-15]. The final neural network structure is 9-36-3, as shown in Figure 2.

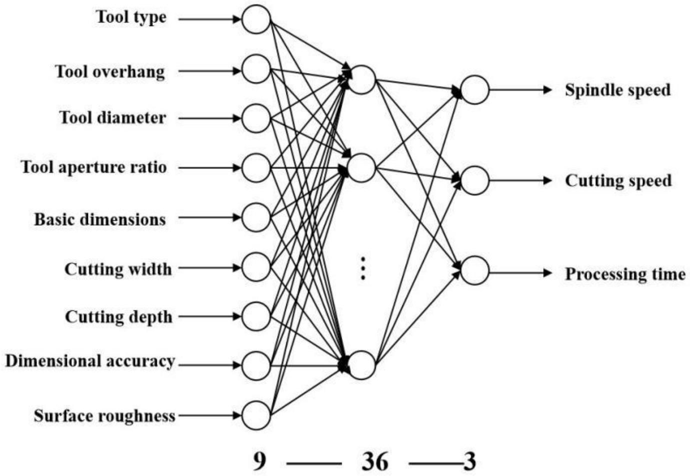

Figure 2: Structure of BP neural network with optimized milling parameters.

4 RESULT ANALYSIS

4.1 BP Neural Network Training Analysis

The numerical control milling parameter optimization model constructed by BP neural network was trained with sample data.

4.1.1 BP neural network training error curve

To train the BP neural network, we need to calculate the weighted input vector of the network and the output of the network and the error vector, and get the sum of the error numbers. Training stops if the sum of the squares of the training vectors is less than 10-4 of the training accuracy; that is, the transformation error is calculated in the output layer, the weights are adjusted by the learning rules of the fallback policy, and the process is repeated. After the training of the neural network is completed, the vector that is not in the training set is the input of the neural network, and the neural network will give the result as a generalization [16-17]. The error curve of BP neural network is shown in Figure 3.

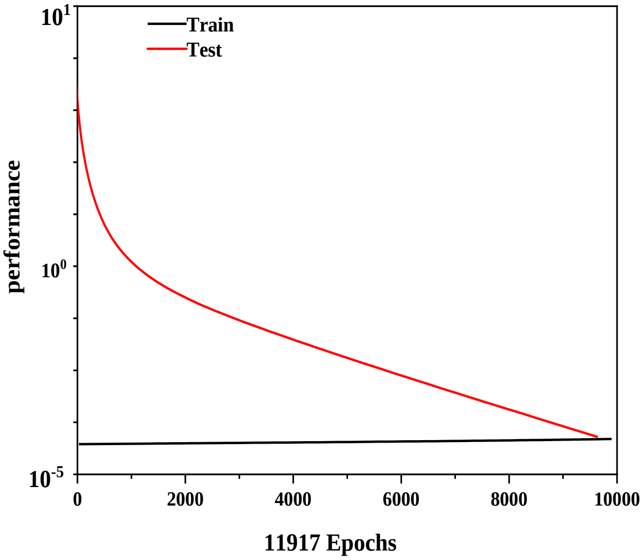

Figure 3: Error convergence curve.

4.1.2 BP neural network performance test curve

The postreg function returns three values. m and b represent the slope and intercept of the regression line, respectively. When m = 1 and b = 0, the output of the neural network is the same as the target output, and the neural network has the best performance. r represents the correlation coefficient between the output network and the output plan. As it approaches 1, the output of the neural network approaches the output and efficiency of the network. Figure 4 shows that the best regression line is almost parallel to the best regression line (the line where the output of the network is equal to the output plot), which indicates that the neural network performs very well [18-19].

4.2 Comparative Analysis of BP Neural Network Prediction and Validation Data

The validation data in the validation sample data table is brought into the trained numerical control machining milling parameter model for verification. The comparative analysis of sample data of spindle speed and predicted data, the comparative analysis of sample data of feed speed and predicted data, and the comparative analysis of sample data of processing time and predicted data are shown in Figure 5, 6 and 7.

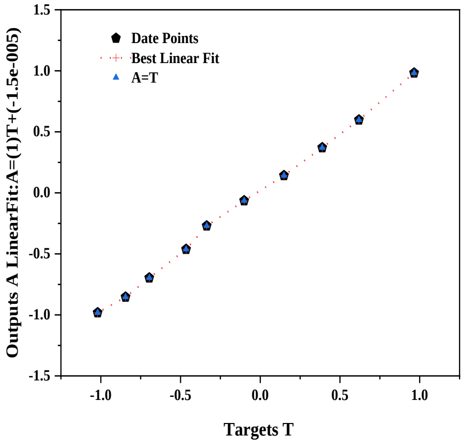

Figure 4: Performance test curve of neural network.

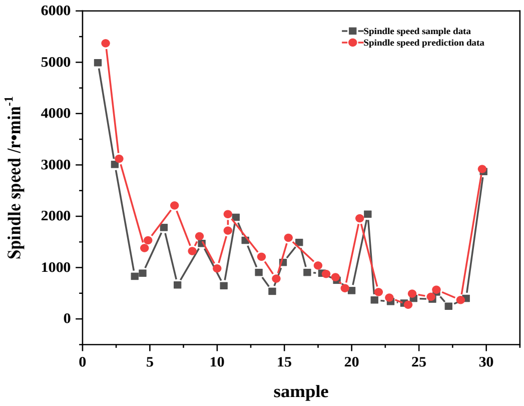

Figure 5: Comparative analysis of sample data and predicted data of spindle speed.

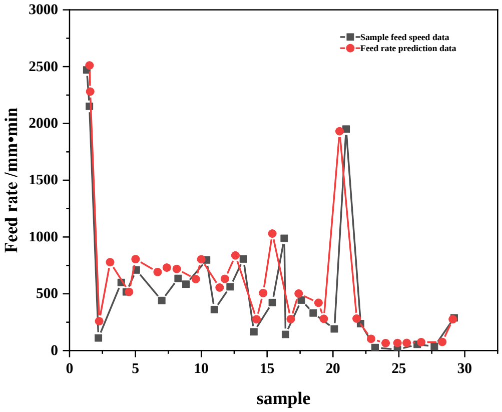

Figure 6: Comparative analysis of sample data and predicted data of feed speed.

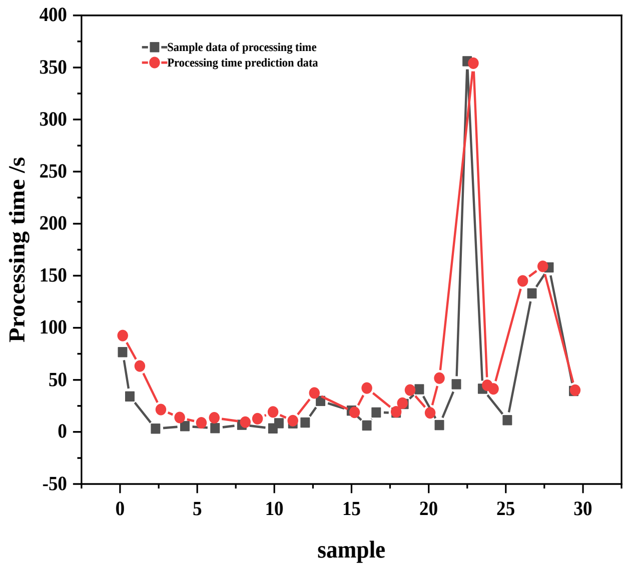

Figure 7: Comparative analysis of sample data and predicted data of processing time.

It can be seen from Figure 5, 6, 7 that the sample data verified by the test is basically consistent with the predicted data of BP neural network, achieving the expected effect of parameter optimization of CNC milling. Artificial neural network is a process of global optimization. It is normal that some individual predicted value is greater than or less than the value of the verification sample data [20-21].

4.3 BP Neural Network Prediction Accuracy

The prediction accuracy of BP network is expressed by the absolute prediction error. Table 2 shows the predicted values and absolute errors of the verified data on spindle speed, feed speed and machining time. Table 2 shows that the maximum absolute error of the spindle speed is 13.3%, the minimum absolute error of the spindle speed is 0.19%, the average absolute error of the spindle speed is 5.51%, the maximum absolute error of the feed speed is 28.21%, the minimum absolute error of the feed speed is 0.39%, and the average absolute error of the feed speed is 3.64%. The maximum absolute error of processing time is 20.10%, the minimum absolute error of processing time is 0.27, and the average absolute error of processing time is 3.89%[22-23].

Predicted value	***Test***	***Absolute error***	***Predicted value***	***Test***	***Absolute error***	***Predicted value***	***Test***	***Absolute error***
5416.9	5000	0.0833	2148.5	2500	0.1636	98.85	84	0.1768
				......				
336.51	350	0.0386	59.33	60	0.0113	106.52	110.4	0.0351
2934.7	2700	0.0869	258.97	260	0.039	39.31	39	0.0079
Mean absolute error		0.0551	Mean absolute error		0.0364	Mean absolute error		0.0389

Table 2: Comparison table of prediction and test error.

5 CONCLUSION

A shell part (made of LD5 forged aluminum) was machined on a DMC60H NC machine tool with a diameter of Φ 14mm. The Φ10mm cylindrical milling cutter is adopted with 45mm suspension, 1mm cutting width, 1mm cutting depth, machining dimension tolerance Φ14+ 00.18mm, surface roughness R_a1.6μm. Firstly, the machining dimension tolerance was converted into the standard tolerance IT12, and then the machining conditions and machining requirements were inputted into the BP neural network to build the numerical control machining milling parameter model. After training, the output milling parameters were: spindle speed 5516r/min, feed speed 1449mm/min, and processing time 12s. Compared with the milling parameters used in the original production site, it not only improves the utilization rate of the machine tool, reduces the cutting time (can be shortened by about 50%), but also improves the processing quality of the workpiece. The actual processing test shows that the original processing of part needs 3312s, after optimization, the processing time of a part is 1628s.

By using the above proposed test data and sample data processing principles, the sample data optimization is realized, and the convergence accuracy and convergence speed of BP neural network model are improved. By using BP neural network to optimize the selection of cutting parameters, the artificial error in the process of selecting cutting parameters can be abandoned, so that the selection of cutting parameters has higher reliability. The technological effect is obvious. This method can improve the production efficiency and reduce the cost, and has good production and promotion value.

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