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Research on Fuzzy Neural Network Modeling and Genetic Algorithms Optimization in CNC Machine Tools Energy Saving

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Abstract. There is a very complex nonlinear relationship between cutting parameters and machine tools energy consumption in CNC machining process. The general formulas are very complex from experience; it needs the experience tables and complex and tedious calculations to estimate energy consumption. This paper proposes a CNC machine tool cutting process model for energy consumption based on adaptive fuzzy neural network because of its very strong nonlinear mapping ability, and then solves the model by using the genetic algorithm due to its ability for global optimization. The optimal combination of cutting parameters is verified its optimization in cutting experiment. As compared with the traditional empirical formula, the proposed method simplifies the calculation of energy consumption and provides a good energy control proposal for CNC machine tool roughing process.

Keywords: CNC Machine Tool, Energy Modeling, Fuzzy Neural Network, Genetic Algorithm

1. Introduction

With the increasingly widespread use of CNC machine tools, the issue for energy consumption in CNC machine processing has become a focus. Because of the flexibility and the high-precision machining capabilities of the CNC machine tool, people pay more attention to the part accuracy and processing efficiency, but ignore the machine's energy consumption. After ensuring the accuracy and efficiency, the cutting process and control strategy can be improved to enhance the CNC machining efficiency and reduce energy consumption, it is significant for the economical and environmental manufacture.

CNC machine tools is a system set including the complexity material information, energy flow and process flow, which relates each other and has its only features, so the analysis and modeling of machine energy issues become very complex [1]. Available researches mainly focused on machine tools electrical modification. The power curves can be calculated by the energy balance equation by continuous testing machine motor input running power, and using statistical data of energy loss in different schedule and different power machine which have the same workpiece in the processing, machine tools and production schedule are reasonable arranged for minimum processing cost of the integrated product [2]. The energy consumption can be reduced the lower level by dynamically adjusting machine noload speed, control method includes shortening transmission time, reducing tool change time, workpiece clamping time and supplementary time [3]. Existing studies have some methods such as using variable-frequence governor to reducing motor starting current, machining with constant power or constant cutting speed, and other ways to reduce energy consumption [4,5].

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This paper proposes modeling a complex system of a energy consumption of the CNC machine tool cutting process by Adaptive Fuzzy Neural Network (FNN). The FNN has very strong nonlinear mapping ability which can automatically summarize the functional relationship between data by learning (or training) without any a priori formula. Then genetic algorithm with its ability of global optimization is used to solve the model. The optimal combination of cutting parameters is verified its optimization in cutting experiment.

2. Energy Analysis of CNC Machining Process

In the actual cutting process, the main energy consumption of CNC machine tools is shown as follows:

1) Spindle rotation energy consumption, which accounts for the majority of machine tool consumption. When the speed is higher, the cutting force is larger, its power demands greater, and the energy consumption is higher.

2) The feed control axis energy consumption is the servo motor energy consumption which mainly caused by feed resistance reaction and the table movement friction. The faster the feed rate is required, the larger the feed reaction resistance is impacted and the higher energy consumption of the servo motor power is demanded. However, the feed velocity can get higher removal rate and shorten the cutting time.

3) Cutting depth also has a greater impact on energy consumption. The larger cutting depth will cause larger cutting force and the greater power is required, so it will cause energy consumption increases. But the large cutting depth can also get a larger removal rate and shorten the cutting time, and shortening the machine movement time.

4) The energy consumption of auxiliary electrical appliance includes tool-exchange operation, the cooling pump operation, chip-removal system operation and so on. In general, the chip-removal action and tool-exchange action are a shorter running time relative to the entire processing of the system, so they are not taken into account in the following calculation. The energy consumption of the cooling pump running is different in the different cutting processing. Based on the same cutting processing, the energy consumption of auxiliary electrical appliance is treated as constant value, only related to the length of processing time.

From the above analysis, it can be seen that the higher spindle speed processing will cause energy consumption higher. The larger cutting depth and cutting speed will cause the larger power needs, but cutting time is shortened, energy consumption what they caused is difficult to evaluate. In addition, the high cutting depth and cutting speed will cause tool wear fast, so how to adopt a good cutting parameter is a problem worthy to study. A lathe cutting schematic diagram is shown in figure 1(a).

3. Fuzzy Neural Network Modeling and Genetic Algorithms

3.1. Fuzzy Neural Network Modeling

Adaptive fuzzy neural network has very strong nonlinear mapping ability. It can automatically summarize the functional relationship by learning (or training) without any a priori formula. It is an effective means of modeling. The ANFIS (Adaptive Network based Fuzzy Inference System) uses neural network learning mechanism to compensate for the shortcomings of the fuzzy control original system, so it can easily expressed human knowledge with fuzzy logic. The ANFIS has the advantages of the nervous network distributed information storage and learning ability. It is an effective tool for complex systems modeling and control provides. Figure 1(b) is a adaptive neural network fuzzy inference system similar to Sugeno fuzzy inference system, which each node in the same layer have similar functions [6].

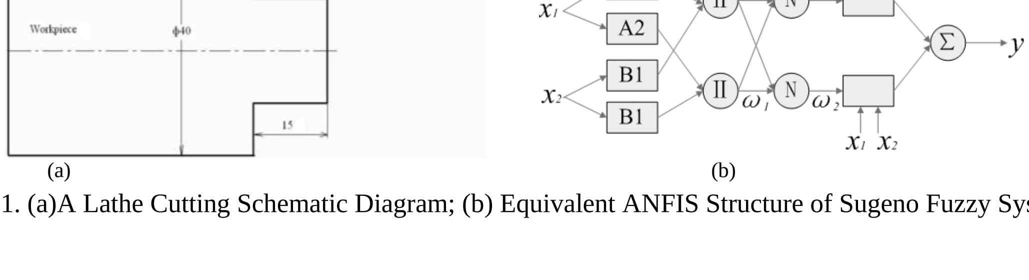

Fig. 1. (a)A Lathe Cutting Schematic Diagram; (b) Equivalent ANFIS Structure of Sugeno Fuzzy System

The first thing is to build the model combined fuzzy systems and neural network. Fuzzy neural network is a fuzzy inference system which its framework is based on a neural network in general.

Assume that the system has n input i (i = 1,2, …, n), output is y, then the fuzzy rules j = 1,2, …, z, the system input and output fuzzy model is:

If x_1 is A_{j1}, x_2 is A_{j2}, x_3 is A_{j3}, …, x_n is A_{jn}, then $y_1=\omega_{j0}+\omega_{j1}\times x_1+\omega_{j2}\times x2,\ldots,+\omega jn\times xn$.

Then the global output of the model can be expressed as:

$$y=\frac{\sum_{j=1}^{n}\lambda_j y_j}{\sum_{j=1}^{n}\lambda_j} \tag{1}$$

Where, i for the input variables and λj is as follows:

$$\lambda_j=\mu_{A_{j1}}(x_1)\wedge\mu_{A_{j2}}(x_2)\wedge,\ldots,\wedge\mu_{A_{jn}}(x_n) \tag{2}$$

Λ is the fuzzy logic and computing, that is, take a small operation; uAjn(x) expresses the fuzzy sets Aji(xi) membership function values. Aji is Gaussian membership function:

$$A_{ji}=\exp\left[-\left(\frac{x_i-c_{ji}}{b_i}\right)^2\right] \tag{3}$$

Where, cji is the center value of membership function; bi is the width of the membership function.

The first layer is the input layer, and each node represents an input variable. In this model there are 3 cutting parameters as input variable. The second layer is fuzzification layer, input variables is blurred through one or more membership function. The third layer is fuzzy condition layer. The layer nodes complete combination of fuzzy rules conditions and realize the fuzzy value of each input "multiply" operation, also known as "and" layer, and the number of nodes are number of the fuzzy rules.

The fourth layer is fuzzy decision layer. The connection relation between this layer node and the third layer nodes represents the conclusions of fuzzy rules. The fuzzy value obtained corresponds to the size of the output node. The fourth layer is "or" layer, the number of nodes is the number of output variable fuzzy ambiguity q. The connection layer and the third layer is fully connected, the connection weight is ω kj, where k = 1, 2, ..., q; j = 1, 2, ..., m × n. The weight represents confidence degree of each rule.

The fifth is for defuzzification layer. The layer nodes change the output value from the fuzzy value to the numerical value and bring output clear. Commonly, the defuzzification method is the maximum defuzzification method, the center average defuzzification method, the center of gravity defuzzification method. Each node is adaptive node. Here the method of defuzzification layer is the weighted sum of the center of gravity method.

3.2. Genetic Algorithm

After a nonlinear system modeling, we often need to solve the objective optimization problem. The Classical optimization method is based on the objective function of the gradient or higher derivative which produces a convergence in the calculation of the optimal solution series, starting from a single point along the direction of steepest descent iteration. In the absence of all of the search solution space, this method easily falls into local optimum.

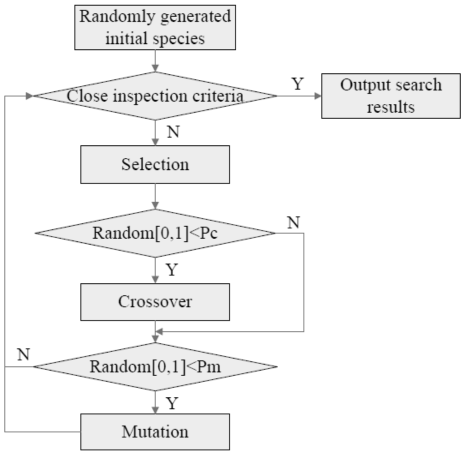

Fig.2. Genetic Algorithm Flow Chart

Genetic Algorithm is an optimal search method simulating a natural evolutionary process. It is constructed with a random population of potential solutions; it is the multi-search method simulating evolution of populations. Its offspring develops toward the direction of improving the living environment ultimately. It can gains the global optimal solution [7]. Genetic algorithm flowchart is as figure 2.

Genetic operation includes three basic genetic operators: selection, crossover and mutation. The three genetic operators have the following characteristics.

The individual genetic operator is carried out under the random disturbance. Therefore, the rule of the individual migration to the optimal solution is random. It should be stressed that this randomized operation is different from the traditional random search method. Genetic operation is a highly directed search, but a general random search method is search for free.

4. Energy Consumption Model CNC Machine Tools and Simulation

4.1. Experimental Data Acquisition

An experiment is designed to obtain the data about CNC machine tool cutting parameters and energy consumption values. The CNC lathe is test object; workpiece chooses ф40 bar, cutting method is round rough processing, tool-path is designed to a simple rectangular path, cutting length is 15mm, Schematic diagram of simulated cutting and rectangular tool-path are showed in Figure 1(a). The CK6136 CNC lathe is selected, and its parameters are as table 1:

Table 1. CK6136 CNC Lathe Power Parameters

Spindle	X-axis	Z-axis	Others	η
5.5KW	1 KW	1KW	0.2 KW	0.75

To calculate the CNC machine tool power consumption in the running course, one of three-phase AC current is measured at the line import of the machine tool, and the time required to complete the same process is recorded. The formula (4) can be used to calculate cutting power and no-load power by the current measured.

$$P = \sqrt{3}UI\cos\varphi \tag{4}$$

In order to facilitate experiments and programming, the depth of cutting is divided into five grades; the feed rate is divided into three grades; and the spindle speed is divided into seven grades. Total of 105 groups data are obtained. 15 groups of samples are randomly selected as testing samples which do not participate in training samples, and the remaining 90 groups of samples are used as training samples. The data after normalized is shown in table 2.

Table 2. Some of The data after normalized

	Input			Output
ID	Cutting speed	Feed Speed	Cutting Depth	Energy Consumption
1	0.90	0.1	0.5	0.89
2	0.87	0.3	0.5	0.98
3	0.684	0.1	0.5	0.815
4	0.672	0.2	0.5	0.825
5	0.66	0.3	0.5	0.831
6	0.64	0.1	0.5	0.825
7	0.62	0.2	0.5	0.83
8	0.60	0.3	0.5	0.835
.	…	…	…	…

4.2. Fuzzy Neural Network Modeling and Training

The MATLAB toolbox is used to model the fuzzy neural network of the machine tool consumption. Here ANFIS toolbox is selected. Input layer has 3 nodes which represent 3 cutting parameters of cutting speed, feed rate and cutting depth. Here, trapezoidal membership function is selected as input membership function.

Generator FIS: Automated rules (default)

The rule is shown as:

If *input1* is *in1mf1* and *input2* is *in2mf1* and *input3* is *in3mf1*, then *output* is *out1mf1*

…,…,…

where, *input1* is 1 input variable,in1mf1 is membership function of 1.

Connection: and

After fuzzy neural network structure is established, load data which is gained from experiment, generate fuzzy inference rule, Training FIS optimize method is set hybrid, and train epochs is set 100 and error tolerance is set 0.012. The ANFIS training result is shown as figure 3(a).

The adaptive fuzzy neural network is trained by using 90 groups of training data gained from experiment above, after 100 epochs training, it reached goal 0.010736, and adaptive fuzzy neural network model has been established for CNC machine tools and cutting energy consumption. The FIS output and training data output is compared in figure 3(b), “o” indicated training data output and “*” indicated FIS output.

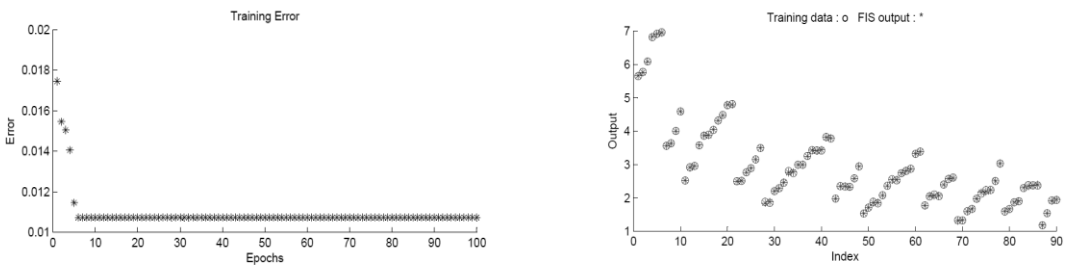

Fig. 3. (a)ANFIS Training Result; (b) FIS Output and Training Data Output

Whether the trained model reflects a better mapping between the CNC machine tool and cutting energy consumption, it is usually evaluated by the generalization ability of the network which is the main indicator of neural network performance. Using already established neural network model, test samples or work samples are on the test, their test errors are gotten to assess its generalization ability.

Using the MATLAB ANFIS, and choosing the test mode,15 test sample data are inputted to model, the output value are compared with the actual value of these 15 samples. The fuzzy neural network output is indicated with the "•" and the actual output is indicated with the "*", the results are shown in figure 4(a).

Using the same method，15 groups of data which do not participate in training samples are used as work groups. Results are obtained as shown in figure 4(b). The results show that the test group average testing error is 0.0086259, the work groups average testing error is 0.02545.

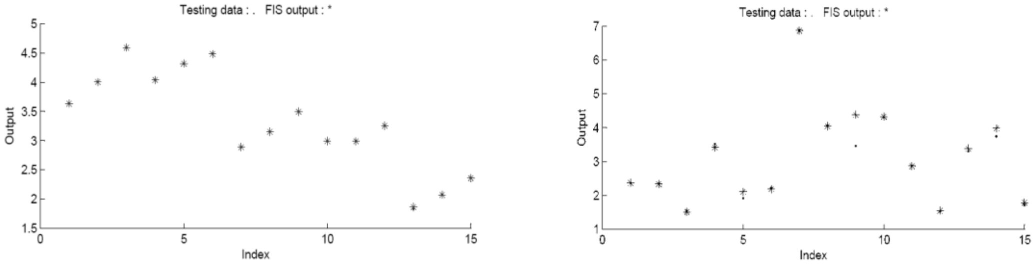

Fig. 4.(a)The Test Samples Testing Result; (b)The Work Samples Testing Result

From the chart above, it is found that the result of test sample participated in the training sample are better than the work sample which not involved in training samples. However, the fuzzy neural network model output error of work samples is small; it is proved that the model has good generalization ability. The target function of the CNC machine tool energy consumption relating to cutting parameters is gotten.

4.3. Cutting Parameters Optimization

The energy consumption system of CNC machine tools needs to solve the overall objective function optimization problem. The effects of genetic operation is closely related to operation probability, coding method, population size, initial population and the fitness function of the three genetic operators.

Genetic algorithm toolbox in MATLAB optimization algorithm is used. The initial population is selected as 20, digit binary code selected as 10, crossover probability selected as 0.7, and mutation probability selected as 0.01. After 300 generations, we get the value of single-objective optimization and the corresponding optimal solution. The best individual is {0.3931, 0.2129, 0.79782}, and its objective value is 1.6425.

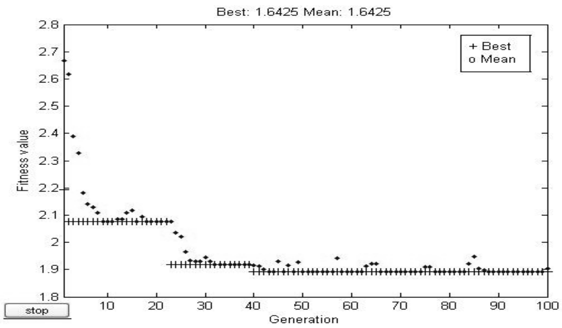

Fig. 5. The Prior 100 Generations Fitness Variation

The data gained above are transformed into cutting parameters. Using the optimized cutting parameters in CNC machine tool to verify, the actual energy consumption is 8.95×10-3KWh. The optimized value compared to experience value is as table 3. It is found that cutting parameter by optimized is much lower energy consumption than the experience value.

Table.3. Energy Consumption Compare Between Optimized Value and Experience Value

Cutting Parameters	Optimized Value	Experience Value
Cutting Speed (m/min)	18.52	100
Feed Speed (mm/r)	0.798	0.2
Cutting Depth (mm)	1.05	1.00
Model output ($\times10^{-3}$KWh)	8.23	13.65
Experiment Value ($\times10^{-3}$KWh)	8.95	14.34

5. Conclusion

By using experimental data, the CNC machine tools energy consumption and cutting parameter function is established based on fuzzy neural network. The model can map the CNC machine tools energy consumption to cutting parameters and have good generalization ability. The method is proved to be effective and simple without complex computer by simulation and experiment.

By genetic algorithm, the parameter of the objective function is optimized. The optimal value is verified its energy consumption by cutting experiment. It is shown that cutting parameter by optimized gets much lower energy consumption than that by the experience value. It provides an important reference for the roughing process of CNC machine tool consumption.

The paper makes a preliminary energy consumption study for only part of the cutting parameters. Because the factors that affect the machine tool energy consumption have tool material and shape, workpiece material, machine tool structure, etc, CNC machine energy-saving research needs to take other factors into account comprehensively in future.

6. Acknowledgements

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