Research on Milling Force Prediction Model Based on Improved Particle Swarm Optimization Algorithm

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ABSTRACT: According to the remarkable characteristics of milling force, an innovative method of milling force modeling using improved particle swarm optimization (PSO) fuzzy system based on support vector machine (SVM) is proposed in this paper. The experiment of titanium alloy milling is designed and implemented. The advanced tester is used to measure the milling force. The training data and test data based on the fuzzy system are obtained. The gradient descent algorithm is embedded in the ordinary particle swarm optimization algorithm to obtain the improved particle swarm optimization algorithm. The convergence effect of the improved particle swarm optimization algorithm is obviously better than that of the ordinary particle swarm optimization algorithm. The improved particle swarm optimization (IPSO) based on fuzzy system is applied to the milling force modeling. Finally, the improved particle swarm optimization (PSO), gradient descent algorithm and improved particle swarm optimization (IPSO) are used to train the fuzzy system, and the conclusion that the final training error of the improved particle swarm optimization (IPSO) is the smallest is obtained.

1. Introduction

Cutting force is the key parameter of the object in the process of cutting processing, and its size directly affects the object's cutting heat, cutting deformation and so on. There are three main vertical components of cutting force: main cutting force, back force and feed force. Modeling cutting force can optimize cutting parameters, effectively control machining deformation, and provide reference for calculating the wear degree of cutting tools. Traditional cutting force modeling methods include mechanical modeling, empirical modeling, intelligent modeling and finite element modeling.

Traditional cutting force modeling methods are mostly aimed at steel, iron, aluminum alloy and other easy-to-process materials. This kind of material for titanium alloy processing complex, because it has the tendency of work hardening and high thermal conductivity characteristics in low titanium alloy cutting, outstanding performance for the cutting force, high tool wear degree and the higher cutting temperature. Moreover, between the cutting force and cutting force parameters there is a complicated relationship. It is difficult for the traditional modeling method of cutting force to correctly simulate the mechanical process. Intelligent modeling method of cutting force can handle more complex nonlinear problems, and has become the key research content in modeling method of cutting force.

The cutting force of intelligent modeling, mainly in the application of BP neural network, extracting key data information by using the BP neural network, prediction model of cutting force. In the field of artificial intelligence, the application of fuzzy system modeling method is not common, but because of the fuzzy system can not only obtain accurate data information, also can realize the expert system. In
this paper, the milling process of titanium alloy is based on the improved particle swarm optimization algorithm, and its application in fuzzy system, to realize the prediction of milling force modeling method.

2. Fuzzy system and improved particle swarm optimization algorithm
Mamdani fuzzy system can effectively compensate for the shortcomings of the traditional universal pure fuzzy systems, Mamdani fuzzy system has been widely applied in many fields such as communication, control. This system is the choice of fuzzy support vector machine, at the same time with singleton fuzzifier, average defuzzifier and Gauss function Mamdani fuzzy system, the mathematical expression of Mamdani fuzzy systems as shown in formula (1).

\[
f(x) = \sum_{i=1}^{M} \prod_{i=1}^{n} \exp \left( - \frac{(x_j - x_j^{-1})^2}{\sigma_i^2} \right)
\]

Where is the number of fuzzy rules is the number of fuzzy rules; some of the conditions; fuzzy rules is part of the membership function parameters; fuzzy set fuzzy rules is part of the THEN center is the input of fuzzy system value.

A fuzzy system, such as formula (1), is designed to ensure the minimum error value of the following training.

\[
e = \sum_{p=1}^{N} \frac{1}{2} \left[ f(x_p^0) - y_p^0 \right]^2
\]

Which is the system of training error; training data number; belongs to the training data input and output items. To sum up, and said, respectively, in order to make the fuzzy system can fully meet the needs of formula (2) in the training of the minimum error, the need for training of fuzzy system parameters. Usually, people in the process of analyzing problem, the basic conclusion is uncertain, therefore, according to the fuzzy rules and formula (1), can determine the fuzzy system parameters are part of the THEN training center by fuzzy sets, the gradient descent algorithm to train as shown in formula (3).

\[
y(q+1) = y(q) - \alpha \frac{\partial e}{\partial y} b
\]

Suppose:

\[
f = \frac{a}{b}, a = \sum_{i=1}^{M} (y z), b = \sum_{i=1}^{M} z^{\frac{-1}{2}}
\]

\[
z^{\frac{-1}{2}} = \prod_{i=1}^{n} \exp \left( - \frac{(x_j - x_j^{-1})^2}{\sigma_i^2} \right)
\]

According to the derivation of Gauss compound function, we can get formula (4).

\[
\frac{\partial e}{\partial y} = \sum_{i=1}^{N} (f - y) \frac{\partial f}{\partial a} \frac{\partial a}{\partial y} = \sum_{i=1}^{N} (f - y) z^{\frac{-1}{2}} b
\]

The formula (4) into the formula (3), the fuzzy rule learning algorithm THEN fuzzy set center as shown in formula (5).

\[
y(q+1) = y(q) - \alpha \sum_{i=1}^{N} (f - y) z^{\frac{-1}{2}} b
\]

Particle swarm algorithm belongs to the group of iterative computation algorithm of artificial intelligence.
environment, which has high robustness, global ability and fast convergence characteristic search. In order to improve the local search ability of particle swarm algorithm, the gradient descent algorithm into particle swarm algorithm, an improved particle swarm algorithm, the new algorithm for each individual particle produced in accordance with the established practice of gradient descent algorithm to calculate the probability.

3. Milling force prediction model based on fuzzy system

In the theory of metal cutting, metal cutting force is related to many factors, including materials, dosage, workpiece and tool, etc. This paper studies the influence of milling parameters on metal, milling force so selected spindle speed, feed rate, radial cutting depth and the axial depth of cut as input and output of the fuzzy system, the metal milling force said.

The metal milling force experiment is studied in this paper based on the realization of the NC milling machine, using three to the dynamometer of the milling force measurement, the cutter is cemented carbide tool, a total of 4 teeth, diameter of spiral angle of milling cutter.

The workpiece foot length and width and height respectively, and TC18 type workpiece materials, cutting fluid in the process of milling in Figure 1 for the test system of metal cutting force.

![Figure 1. Schematic diagram of cutting force test system](image)

This paper is a study of metal milling force milling force of the finishing process, in accordance with the range of cutting parameters and orthogonal principle, orthogonal experimental design (4 factors and 4 levels), correlation factor and level selection as shown in table 1. During the experiment, the cutting parameters of metal are shown in Table 2. The sample data obtained from experiments can be used as the sample space characteristics, the fuzzy system as training data, at the same time, on the completion of the 4 group and the orthogonal experiment with different experimental principle, the results are shown in Table 3, and the fuzzy system as test data.

**Table 1. Factors and levels of experiment**

| Factor                        | 1   | 2   | 3   | 4   |
|-------------------------------|-----|-----|-----|-----|
| Spindle speed \( n/(r \cdot \text{min}^{-1}) \) | 600 | 800 | 1000| 1200|
| Feed speed \( v_f/(\text{mm} \cdot \text{min}^{-1}) \) | 100 | 120 | 200 | 250 |
| Radial cutting depth \( a_e/\text{mm} \) | 1.0 | 1.5 | 2.0 | 2.5 |
| Axial cutting depth \( a_p/\text{mm} \)     | 0.2 | 0.3 | 0.4 | 0.5 |

**Table 2. Cutting force parameters of experimental data**

| Experimental number | axial depth \( a_p/\text{mm} \) | radial depth \( a_e/\text{mm} \) | spindle speed \( n/(r \cdot \text{min}^{-1}) \) | feed speed \( v_f/(\text{mm} \cdot \text{min}^{-1}) \) |
|---------------------|---------------------------------|---------------------------------|---------------------------------|---------------------------------|
| 1                   | 0.2                             | 1.0                             | 800                             | 100                             |
| 2                   | 0.2                             | 1.5                             | 600                             | 150                             |
In order to avoid the error produced in the course of the experiment, this paper has carried out 3 experiments in the same way; a total of 48 sets of training data and 12 sets of fuzzy systems, the results are as shown in Table 3. The maximum milling force in each cycle is respectively.

### Table 3. Testing data based on fuzzy system

| Training data | 1  | 2  | … | 12 |
|---------------|----|----|----|----|
| Axial cutting depth $a_p$ / mm | 0.2 | 0.2 | … | 0.2 |
| Radial cutting depth $a_r$ / mm | 1.0 | 1.5 | … | 2.5 |
| Spindle speed $n$ / $(r \cdot \text{min}^{-1})$ | 800 | 600 | … | 800 |
| Feed speed $v_f$ / $(mm \cdot \text{min}^{-1})$ | 100 | 150 | … | 200 |
| Milling force $F_{xm}$ / N | 17.61 | 20.10 | … | 31.26 |
| Milling force $F_{ym}$ / N | 48.33 | 56.33 | … | 65.31 |
| Milling force $F_{zm}$ / N | 18.53 | 26.16 | … | 32.56 |

In Figure 2, the milling force convergence of the 3 directions of the integrated display, it can be seen from the figure, the improved particle swarm algorithm to train the fuzzy system's actual convergence is better than gradient descent algorithm and particle swarm algorithm. The milling force direction, the fuzzy system is trained using the improved particle swarm algorithm, the training error is derived, descent algorithm to train the fuzzy system with the gradient, the training error is derived, using particle swarm algorithm to train the fuzzy system, the training error is. The milling force direction, the training error obtained using improved particle swarm optimization algorithm for training, get the error reduction algorithm and particle swarm algorithm based on gradient and. The milling force direction, the training error is obtained by using the improved particle swarm optimization algorithm for training, get the error reduction algorithm and particle swarm algorithm based on gradient and.
Among them, the local search ability of particle swarm algorithm is better than gradient descent algorithm, and the global searching ability of PSO is better than gradient descent algorithm, improved particle swarm algorithm combining the advantages of two algorithms and overcomes the disadvantages of a single algorithm, obtain the optimal searching ability, the minimum training error.

5. Conclusion
In summary, based on the research of milling force prediction model, the gradient descent algorithm into particle swarm algorithm, forming a new improved particle swarm optimization algorithm, using titanium alloy as an example, The training data and test data of the fuzzy system are obtained by measuring instrument. Gradient descent algorithm, particle swarm optimization algorithm and improved particle swarm optimization algorithm are used to train the fuzzy system respectively. The simulation results show that the improved particle swarm optimization algorithm has good convergence performance, which is obviously superior to gradient descent algorithm and particle swarm optimization algorithm.

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