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The Application of GA-BP Algorithm in Prediction of Tool Wear State

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Abstract. In CNC shaping milling machine, the prediction of the state of tool wear has important application significance to improve productivity, reduce scrap rate and avoid security risks. In this paper, the detection and control system of disk milling cutter is set up by the current monitoring method, the input characteristic quantity and target characteristic quantity of BP neural network for tool wear diagnosis are measured, and the disk milling cutter wear condition prediction neural network is established based on the GA-BP algorithm. At last, the online prediction of milling cutter wear state is realized. The network test results show that the prediction rate of tool wear condition is more than 92.78%.

1. Introduction

At present, the domestic and foreign scholars have done a lot of research on monitoring tool wear. According to the principle of cutting tool wear detection, it can be divided into direct and indirect monitoring [1]. The indirect monitoring method mainly includes cutting force method, vibration signal method, acoustic emission method and power method [2].Compared with direct detection method, the indirect monitoring is easier to realize on-line monitoring, so it is more and more widely used in engineering practice. Among them, the current monitoring is a kind of power detection method, which is mainly based on the relationship between tool wear, cutting force, motor torque, motor power and motor current.

The cutting tool state signal is the only carrier to reflect the cutting state [3]. The domestic and foreign scholars mainly focus on the tool wear signal processing methods which include wavelet analysis, neural network, and threshold judgment and information fusion technology [4]. The neural network mainly through some basic functions of simulation of biological neurons (i.e., neurons), a neural network according to different links organized, so as to realize the fault detection and diagnosis, data feature extraction and information prediction function. Because of the influence of many factors on the wear state of the disc shaped milling cutter, and these factors are nonlinear and fuzzy, the neural network technology has a unique advantage. Based on B-spline function, the B-spline fuzzy neural network is used to calculate the tool wear, and the problems of slow learning speed, low accuracy and low recognition accuracy were solved [5]. In 2006, Onder Yumak put forward a kind of online monitoring method of tool wear which based on the adaptive fuzzy inference. The fuzzy rules are used to study the structure of neural network, in order to determine the optimal value [6]. Chen Jie got the input variables of BP neural network, established the tool wear diagnosis model of the disc shaped milling cutter, and realized the online prediction function of disc forming cutter [7].BP neural network tool wear prediction model of which prediction error is not more than 5.4% is established, and the cutting parameters of cutting tool wear were optimized with the minimum tool wear, based on the genetic algorithm. The optimization results show that the cutting parameters are reduced 6.734% [8].

2. Design of control system for disk shaped milling cutter

In order to monitor the wear condition of the cutter, the hardware platform of the monitoring system is needed to be constructed. The hardware platform includes the processing platform, the current sensor, the data acquisition device, the computer and so on. The main function of the hardware platform of the system is to collect the spindle motor current signal through the sensor, and then the analog current signal is converted into a digital signal which can be identified by the data acquisition card. At last, the signal is transmitted to the computer through the data bus. Current sensor type is YDF-I-A4-P1-04. The data acquisition card is Advantech USB471. Data bus is USB. The detection system software is Lab VIEW. The overall structure of the hardware is shown in Figure 1.

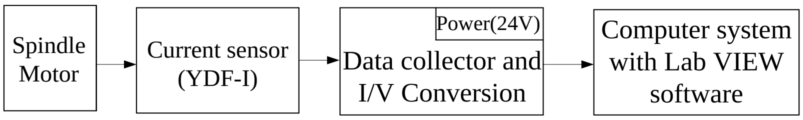

Figure 1. The blade figure of disk milling cutter

Based on the virtual instrument software Lab VIEW developed by NI Company, the wear current detection system of disc forming cutter is developed. The detection system is mainly composed of the equipment selection, channel setting, signal display and preservation, signal analysis, print report forms and alarm components.

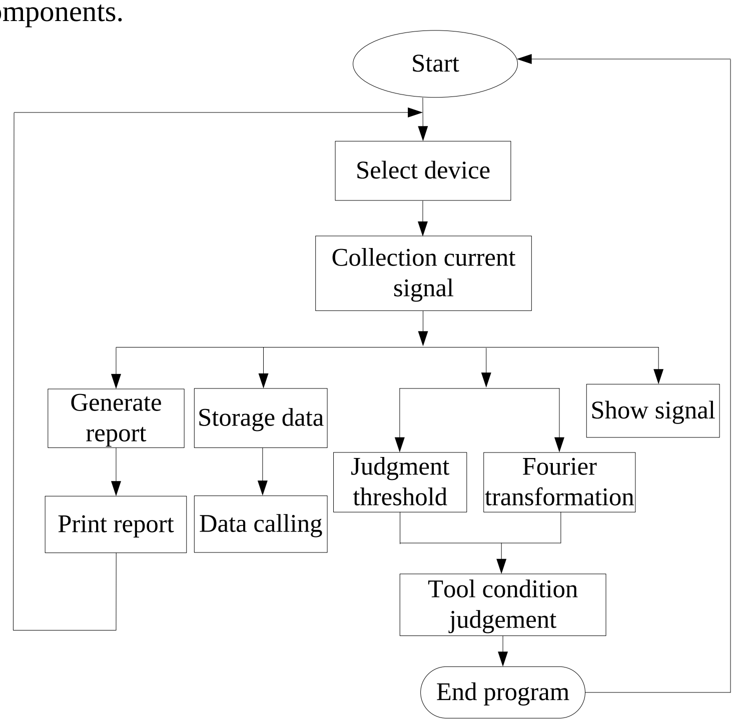

Figure 2. Test system software flow chart

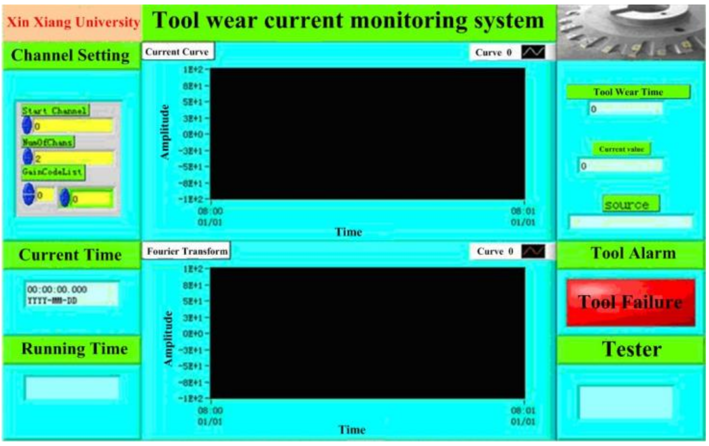

Figure 3. Test system front panel diagram

3. Wear prediction modeling of disk shaped milling cutter

3.1. GA-BP neural network theory

Based on the effect on the chromosome number string, the genetic algorithm (GA) is coded. Then, a group of strings are used to simulate the biological genetic and evolutionary optimization, so as to realize the global search [9]. The Back Propagation algorithm is a feed forward network. Its essence is through the dynamic adjustment of the weights and thresholds to achieve the input and output nonlinear mapping function of height. However, when the initial weight is not suitable, the network will be trapped in local minimum and the convergence rate is too slow [10]. According to the shortcomings of BP neural network, GA algorithm is used to optimize the initial weights and threshold values of input layer, hidden layer and output layer. Furthermore, the wear identification model of GA-BP disc forming cutter is established.

Figure 4. The test site

3.2. Input and target feature vector selection

The Figure 4 is the gear ring cutting test site. In this experiment, the milling machine tool is SKXC-2500W-C. The machining gear parameters are as follows. the work piece material is 50Mn. the surface hardness of gear is HB206-262. The modulus of the gear is 12mm. The number of teeth is 118. the pressure angle is 20°. Tooth height is 100mm. The coefficient of variation is +5mm. Kenna CNC blade model is KC935M. The disc cutter speed is 9r/min, and the feed rate is 140mm/min.

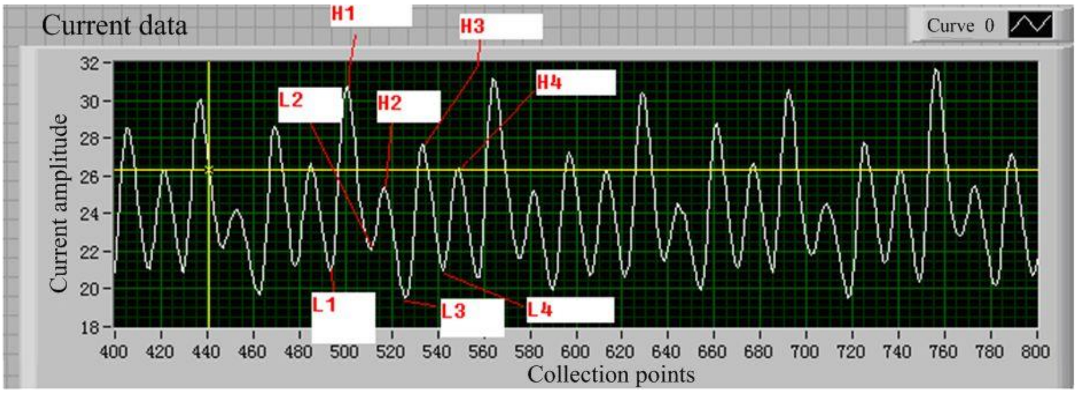

Figure 5. The distribution figure of feature vector

Figure 5 is the distribution of the characteristic vector of the current waveform. In the Figure, the L1, L2, L3, and L4 represent the current value of the lowest point of the current and the next group cutter, the H1, H2, H3 and H4 represent the highest point of the current and the next group cutter. In this paper, L1, H1, L2, H2, L3, H3, L4, H4 are used as input feature vectors of BP neural network. According to the relevant theory of literature 11, this paper defines the formation of the milling cutter as three states which are the primary abrasion (VB=0~0.2mm), normal abrasion (VB=0.2~0.5mm), and sharp abrasion (VB > 0.5mm). In this paper, three kinds of wear states of milling cutters are selected as the feature vectors of BP neural network.

3.3. Sample data acquisition and processing

According to the above experimental conditions, the application of YDF-I-A4-P1-04 current sensor and advantech USB4711 data acquisition card is used to obtain the current waveform of disc cutter in the milling process. Then, the tool wear at different wear time was measured with the ultra depth of field microscope VHX-2000. Because the input variables of BP neural network must belong to [0, 1], it is necessary to normalize the input variables.

$$x' = (x - x_{\min})/(x_{\max} - x_{\min}) \tag{1}$$

In the formula, x' represent the normalized sample data. $x_{\max}$ represents the collected sample data. represents the maximum value of sample data. $x_{\min}$ represents the minimum value of sample data.

Table 1 is the normalization of the current amplitude. Table 2 is the normalized test sample data.

Table 1. The normalized sample data of disk milling cutter

NO	L1	H1	L2	H2	L3	H3	L4	H4	Wear state
1	0.2537	0.12799	0.03647	0.048	0.03049	0.04616	0.00326	0.13136	Primary abrasion
2	0.23880	0.072	0.03951	0	0.02711	0.08392	0.07843	0.23306	
3	0.20149	0	0.04599	0.088	0.02372	0.06085	0.00981	0.12711	
4	0.16418	0.00801	0.02127	0.10134	0.07796	0.06504	0.00654	0.19915	
5	0.27612	0.06398	0	0.072	0	0.02518	0.04576	0.33899	
6	0.16791	0.48	0.36170	0.31467	0.18983	0.67768	0.31698	0.42796	Normal abrasion
7	0.1753	0.568	0.35562	0.42667	0.16949	0.61684	0.29085	0.38984	
8	0.14179	0.62401	0.31307	0.41067	0.21356	0.58746	0.26798	0.37712	
9	0.13805	0.51992	0.29787	0.34934	0.21694	0.69237	0.31046	0.43221	
10	0.17164	0.54	0.32523	0.35466	0.17288	0.61893	0.3333	0.37712	
11	0.89551	0.812	0.95137	0.94134	1	0.95043	0.97712	0.73729	Sharp abrasion
12	0.86566	0.80399	0.92401	1	0.96949	0.91476	0.92808	0.86018	
13	0.87686	0.78801	0.89665	0.86399	0.94238	0.99659	0.91503	0.87712	
14	1	1	1	0.90933	0.91865	0.91267	0.91176	0.79237	
15	0.87312	0.89196	0.93920	0.99734	0.98983	0.98819	1	1	

Table 2. Test datas

NO.	L1	H1	L2	H2	L3	H3	L4	H4	Wear state
1	0.2276	0.0200	0.1337	0.0613	0.0102	0	0	0.1992	primary abrasion
2	0.1119	0.6880	0.4316	0.4320	0.2475	0.5812	0.2614	0.4153	Normal abrasion
3	0.8209	0.8880	0.9088	0.9277	0.9831	1	0.9673	0.8729	Sharp abrasion

3.4. The design of neural network model

GA-BP neural network algorithm mainly includes three parts. They are the creation of BP neural network, genetic algorithm to optimize the initial weights and thresholds of BP neural network, and the BP neural network training and prediction [12].

In this paper, a three layer BP neural network with a hidden layer is selected. On the one hand, the three layer BP neural network, which contains a hidden layer, can approach any rational function in theory. Increasing the number of layers can further reduce the error and improve the accuracy, but it can make a complex network, increase the training time. On the other hand, the error precision can be increased by the number of hidden layer nodes to achieve the training effect than increasing the number of layers is easier to observe and adjust. Therefore, the BP neural network with a hidden layer is usually considered.

From the previous section, The BP neural network input layer has 8 neurons, and the output layer has 3 neurons. Therefore, the number of neurons in the hidden layer is 17=2×8+1. The number of weights is 187=8×17+17×3. The threshold number is 20=17+3. The topology of BP neural network is shown in Figure 6.

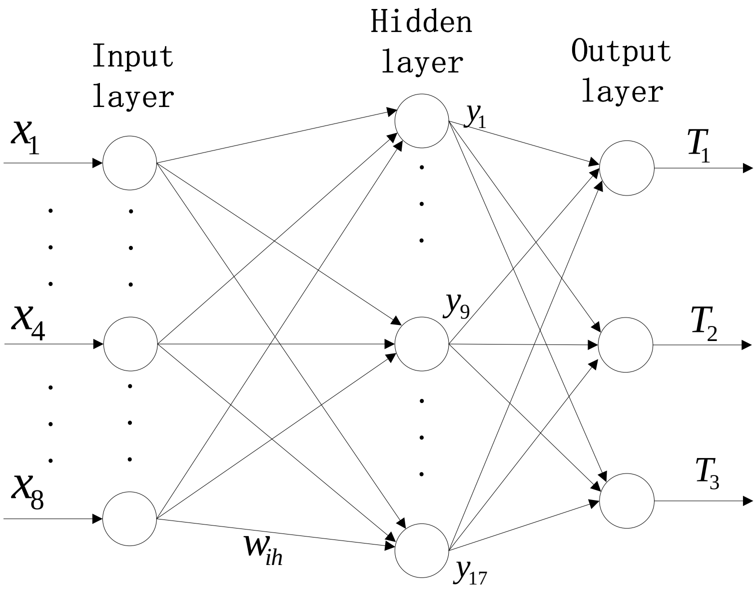

Figure 6. BP neural network topology

The transfer function of hidden layer is the tangent function Tansig (), and the transfer function of output layer is logarithmic function logsig ().The network is trained by using the trainlm() function Levin Berg Marquardt algorithm. The output mode of network is 0 or 1, and the tool wear condition corresponding to the primary abrasion (1, 0, 0), normal abrasion (0, 1, 0), and sharp abrasion (0, 0, 1). BP neural network code is as follows.

```
threshold=[0 1;0 1;z 1;0 1;0 1;0 1;0 1;] % Setting the threshold range
net=newff(threshold,[17,3],{'tansig','logsig'},'trainlm') % Creating The BP neural network
net.trainParam.epochs=1000 % Setting the training times
net.trainParam.show=2 % Setting the display training results frequency
```

net.trainParam.mc=0.9 % Setting the momentum coefficient
net.trainParam.goal=0.01 % Setting performance goals
LP.lr=0.15 % Setting the learning rate
net=train(net,P,T) % Training BP neural network
P and T are the input vector and the target vector. P is the data in table 3.
Genetic algorithm optimization BP neural network mainly includes population initialization, fitness value calculation, individual choice, individual crossover and individual variation. The key part of genetic algorithm code is as follows.
ObjV=sim (net, (bs2rv (Chrom，FieldD))’) % Setting objective function
FitnV=ranking (-ObjV) % Setting individual fitness function
SelCh=select (sus, chrom, FitnV, GGAP) % Setting the individual choice rule
SelCh=recombine (xovsp，SwlCh，0.8) % Setting individual crossover probability
SelCh=mut (SelCh) % Setting probability of individual variation
variable=bs2rv (SelCh，FieldD) % Decimal conversion of offspring
In the Matlab environment, by using the GATBX genetic algorithm toolbox, GA-BP neural network algorithm is established. The algorithm flow is shown in Figure 7.

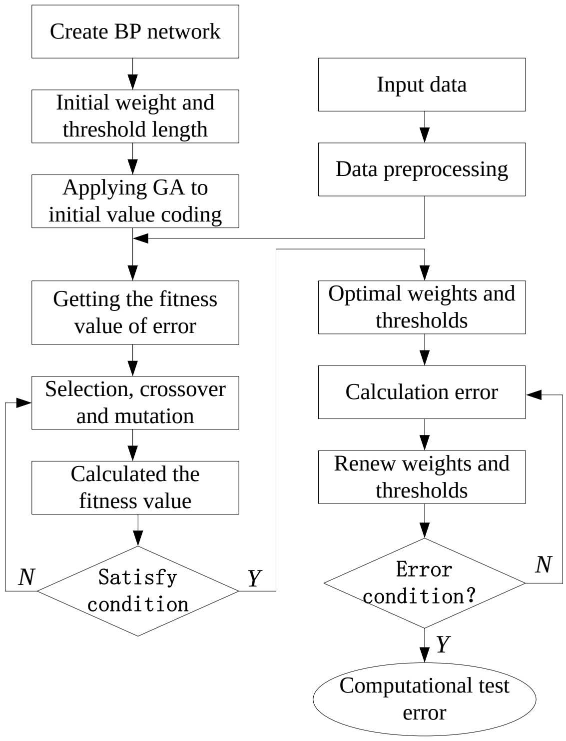

Figure 7. The process for genetic algorithm to optimizing BP neural network algorithm

4. Neural network network training and test results analysis

Based on the 15 sets of normalized sample data in the Table 1, the GA-BP neural network is trained to establish the relationship between the input feature vector and the tool wear state. The weights and thresholds of the training error curve are shown in Figure 8.

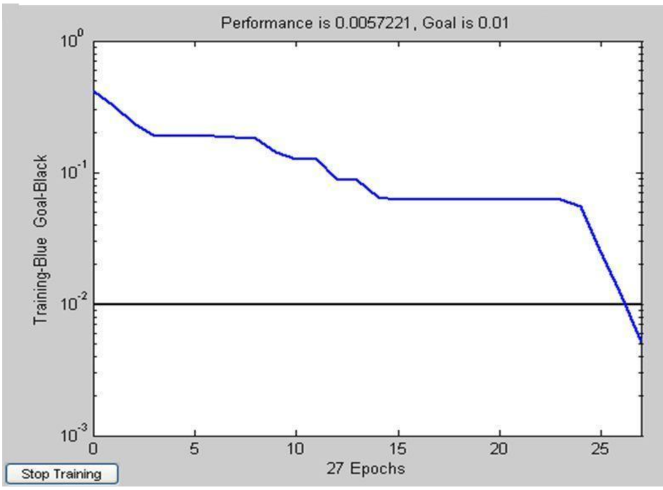

Figure 8. The sketch of training error convergence

In the Figure 8, the fitting accuracy of GA-BP neural network model can reach 0.0057221. The accuracy can meet the needs completely. Then, the 3 groups of new sample data are selected to test the trained GA-BP neural network. The test data are shown in Table 2. Test results and diagnostic rates are shown in Table 3. As can be seen from Table 3, the results show that the tool wear state is consistent with the actual state, and the prediction rate is above 92.78%.

Table 3. Test results

NO.	Ideal output				Actual output				accuracy rate
1	1	0	0	0	0.9945	0.0004	0.0008	0.0077	99.17
2	0	1	0	0	0.0053	0.9634	0.0523	0.0105	95.97
3	0	0	1	0	0.0141	0.0554	0.9640	0.1193	92.78
4	0	0	0	1	0.0045	0.0188	0.0136	0.9982	99.21

5. Conclusion

In the practical application of the disc milling cutter, it is impossible to achieve online wear state prediction. In this paper, based on the current detection method, the Lab VIEW software is used to build the detection system of the disc milling cutter. The neural network normalized training samples of the input features and the target features are obtained. The BP neural network tool wear prediction system is used to be optimized by using the genetic algorithm. The results show that the GA-BP neural network can predict the milling cutter wear state by more than 92.78%, and have a good practical application value.

6. References

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