Research Article

Intelligent Recognition Method of Turning Tool Wear State Based on Information Fusion Technology and BP Neural Network

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The multi-information data acquisition system of tool wear condition of CNC lathe is built by acquiring the acoustic emission and vibration acceleration signals. The data of acoustic emission and vibration acceleration signals during the process of CNC machine tool processing under the conditions of different tool wear degrees and different cutting conditions are acquired and analyzed using the orthogonal experimental method. The optimum characteristic frequency band of acoustic emission and vibration acceleration signals was extracted by the wavelet envelope decomposition method so as to recognize tool wear condition as the characteristic parameters. The characteristic information of acoustic emission and vibration acceleration signals during the process of CNC machine tool processing was fused. In addition, the intelligent recognition of tool wear condition during the process of machine tool processing was researched.

1. Introduction

Tool wear and breakage will occur in the process of CNC machine tool cutting, which will directly affect the machining accuracy and surface quality of the workpiece. Tool wear and breakage will also directly affect the machining efficiency and cutting stability of the whole manufacturing equipment system. According to statistics, the failure shutdown rate caused by tool failure accounts for about 22.4% of the total failure shutdown rate of CNC machine tools. In the actual production process [1], there is a highly nonlinear relationship between the influencing factors and the tool wear [2], so it is difficult to judge the tool wear accurately by the manual method. In order to ensure the accuracy of machining, it is necessary to replace the tool before the tool is severely worn, so it is necessary to replace the tool frequently, but the frequent replacement of the tool reduces the efficiency of production and improves the cost of machining. If the serious situation of tool wear and damage is not found in time or the tool is not replaced in time, the processing process may be interrupted, and the workpiece may be scrapped. By monitoring and identifying the tool

wear status, the tool can be replaced at the right time. Monitoring, identifying the tool wear status, and timely replacing the tool not only can ensure the machining accuracy but also can improve the tool utilization and reduce the production cost. Replacing the cutting tool at the right time can avoid the scrapping of the workpiece and the failure of the machine tool caused by the failure of the cutting tool.

In recent years, many experts and scholars have studied the methods to identify the tool wear state [3–9], and their research has promoted the development of tool wear state identification technology. However, many experts and scholars study the tool wear state identification method based on the information provided by a single sensor, and it is difficult to ensure that a single sensor provides correct and comprehensive information. Information fusion technology is a comprehensive decision-making process to accurately estimate the measurement results of multiple sensors, so as to comprehensively and timely evaluate the situation, threat, and importance. Therefore, information fusion technology has the advantages of high fault tolerance, complementarity, economy, and being real time [10–17]. In recent years, information fusion technology has been applied more and

more in the field of tool wear state recognition, but there is no unified standard [18–22].

At present, the common methods of multi-sensor data fusion can be summarized as random and artificial intelligence. Artificial intelligence includes fuzzy logic reasoning, neural network, and so on. The representation and processing of information by fuzzy logic reasoning is closer to the way of human thinking, but there are many subjective factors in the description of information, so the representation and processing of information by fuzzy logic reasoning lacks objectivity. Neural network has strong fault tolerance, self-learning, self-organization, and self-adaptive ability. It can simulate complex nonlinear mapping and meet the requirements of multi-sensor data fusion technology. In this paper, BP neural network technology is used to fuse the acoustic emission (AE) signal of tool wear and the characteristic information of vibration signal in the process of numerical control cutting, so as to study the intelligent recognition technology of tool wear state in the process of numerical control turning.

2. Acquisition System of Tool Wear Condition

2.1. The Structure of the System. The acquisition system of tool wear condition is composed of a CNC lathe, workpiece, turning tool, AE sensor, vibration sensor, amplifier, signal conditioner, data acquisition card, and computer (the structure diagram of the system is shown in Figure 1).

The AE sensor and vibration sensor are placed in the tool handle. The signal detected by the sensor is processed by the preamplifier and signal conditioner and then transmitted to the computer by data acquisition card for analysis and processing. Figure 2 shows the physical diagram of the multi-information data acquisition system of tool wear condition of the CNC lathe, which is composed of a CKJ6152 CNC lathe, PCI-8 acoustic emission instrument, WD/FM01 broadband differential AE sensor, LC0151T acceleration sensor, LC0201-5 signal conditioner matched with acceleration sensor, and PCI8510 data acquisition card. The signal-to-noise ratio of the acoustic emission instrument is 4.5, the frequency range is 1 kHz–3 MHz, and the maximum sampling frequency is 10 m/s. The AE sensor collects the voltage signal, the measurement range is 1 kHz –1 MHz, and the resonant frequency is 531.25 kHz. The sensitivity of the acceleration sensor is 150 mV/g, the measurement range is 33 g, the resolution is 40 kHz, the resonant frequency is 0.0002 g, and the frequency range is 0.7 Hz–13 kHz. And the 8-channel data acquisition card with the speed of 500 k/s is adopted is 500 k/s.

2.2. The Location of Sensors. The vibration sensor and AE sensor are fixed on the new turning tool of CNC lathe according to different directions and distances. The material of the turning tool is YT15. The turning test of 45# steel bar is carried out under the conditions of spindle speed

$n = 800$ r/min, feed rate $f = 40$ mm/min, and back engagement ap = 0.5 mm. The signals of vibration sensor and AE sensor are collected and analyzed to determine the reasonable fixed position of the sensor.

As shown in Figure 3, the AE sensor is tested in five installation positions. Position 1 is 15 cm from the tip at the rear of the left side of the handle, position 2 is 4 cm from the tip at the front of the left side of the handle, position 3 is 2 cm from the tip at the right side of the handle, position 4 is 4 cm from the tip at the right side of the handle, and position 5 is 6 cm from the tip at the right side of the handle. We find the root-mean-square value of data collected by AE sensor and judge the strength of signal according to the value of root-mean-square value. The results show that the root-mean-square values of positions 3, 4, and 5 decrease in turn, while the root-mean-square values of positions 2 and 4 are basically the same, indicating that the signal strength is independent of direction, while position 1 has the smallest root-mean-square value. Therefore, the best installation position for the AE sensor is position 3.

As shown in Figure 4, the acceleration sensor is tested in three different positions: position 1 is 4 cm away from the tip, position 2 is 8 cm away from the tip, position 3 is 12 cm away from the tip, and the three spatial positions are shown in X, Y, and Z directions in Figure 4. The results show that position 1 and Z direction have the largest root-mean-square value, so position 1 and Z direction are selected as the best installation position for acceleration sensor.

2.3. Dividing the Degree of Tool Wear. One kind of indexable cemented carbide tool CNMG120404-PM and 45# steel bar are selected as test objects. And the parameters of the tool CNMG120404-PM are as follows: tool material YT15, tool rake angle $\gamma = 11°$, clearance angle $\alpha = 10°$, tool cutting edge angle Kr$' = 95°$, tool cutting edge inclination angle $\lambda = 0°$. Cutting tests are carried out according to engagement ranging from 0.3 mm to 1.0 mm to obtain tool test samples of different wear degrees.

During the turning process, the wear of the flank surface has a great influence on the quality of the workpiece, cutting force, and cutting temperature. Since the wear of the flank surface is easy to observe and measure [23], according to the international standard ISO 3685-1977, the wear band width VB measured at the middle part of the flank surface is selected as the test standard, and the tool wear state is divided into 4 wear degrees as shown in Table 1.

2.4. Orthogonal Experimental Method. Taking the tool wear degrees, spindle speed, feed rate, and cutting depth as the main factors, four kinds of blade samples with different wear degrees were selected, and 16 groups of turning experiments were carried out by the orthogonal experimental method. The AE signal and vibration signal were collected in each group of tests, and the influence degree of different factors on AE signal and vibration signal was analyzed.
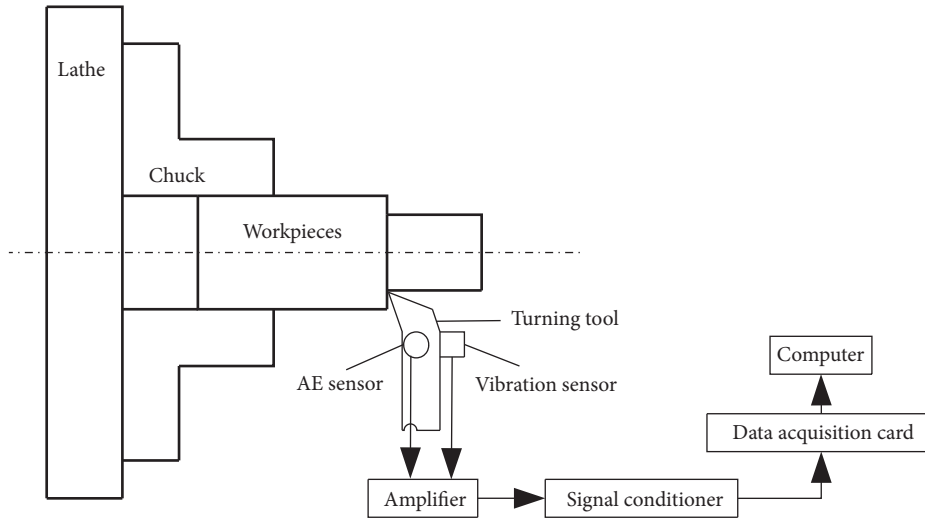
FIGURE 1: The structure diagram of the system.

FIGURE 2: The physical diagram of the multi-information data acquisition system of tool wear condition of CNC lathe.

FIGURE 3: Installation position of AE sensor.

FIGURE 4: Installation position of acceleration sensor.

TABLE 1: Tool wear degrees.

Classification	Initial wear	Normal wear	Medium wear	Severe wear
Degrees	1	2	3	4
VB values (mm)	0~0.1	0.1~0.3	0.3~0.6	0.6~

The test conditions are cutting with cutting fluid. The material processed is 45# steel bar, and the experimental time of each group is 30 s.

Table 2 shows the experimental parameters and the data collected by the sensor, and Table 3 shows the analysis results of the experimental data using the mean method.

According to the analysis results in Table 3, for AE signal, the maximum range of wear degree is 1.9357, the maximum range of spindle speed is 2.5541, the maximum range of feed speed is 0.3083, and the maximum range of cutting depth is 0.5408. Therefore, the spindle speed has the most significant effect on AE signal, followed by wear degree and cutting depth, and the feed speed has the least effect on AE signal. For vibration signal, the maximum range of wear degree is 0.5346, the maximum range of spindle speed is 0.2944, the maximum range of feed speed is 0.2650, and the maximum range of cutting depth is 0.1615. Therefore, the influence of wear degree on vibration signal is the most significant, followed by spindle speed and feed speed, and the influence of cutting depth on vibration signal is the least.
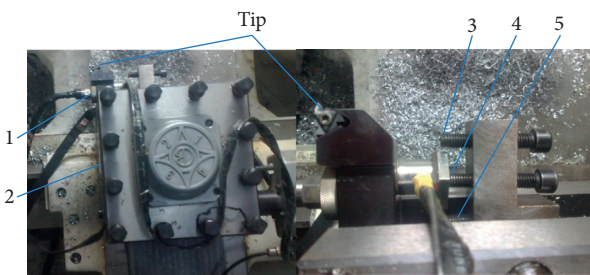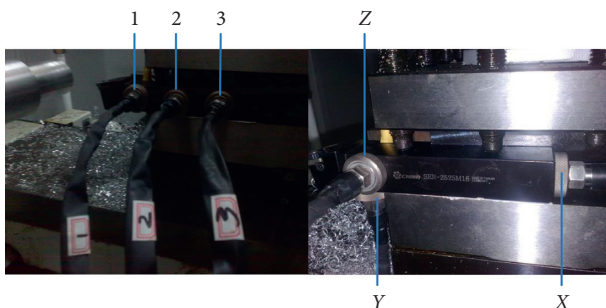
3. Selection of Tool Wear Characteristics

Acoustic emission and vibration signals are nonstationary random signals whose frequency and statistical characteristics vary with time. Spectrum analysis can analyze the characteristics of nonstationary random signals in a certain period. Wavelet packet analysis is a kind of signal processing technology, which concentrates the information energy, finds the order in the details, and selects the rules, and it can divide the frequency band into multiple levels and can adaptively select the corresponding frequency band according to the

TABLE 2: Experimental parameters and collected data.

Serial numbers	Degrees of wear	Experimental parameters			Collected data	
		Spindle speed (r/min)	Feed rate (mm/min)	Cutting depth (mm)	AE sensor (V)	Vibration sensor (V)
1	1	560	20	0.4	0.7522	0.1542
2	1	800	30	0.6	1.4141	0.1732
3	1	1120	40	0.8	2.0434	0.2119
4	1	1600	50	1.0	3.1657	0.2183
5	2	560	30	0.8	1.1045	0.3117
6	2	800	20	1.0	1.9643	0.2944
7	2	1120	50	0.4	1.7929	0.2357
8	2	1600	40	0.6	3.9895	0.2698
9	3	560	40	1.0	2.3615	0.4471
10	3	800	50	0.8	3.3478	0.3960
11	3	1120	20	0.6	4.4762	0.1940
12	3	1600	30	0.4	4.9327	0.2112
13	4	560	50	0.6	2.0609	1.2597
14	4	800	40	0.4	2.2999	0.6498
15	4	1120	30	1.0	4.0951	0.3535
16	4	1600	20	0.8	4.4076	0.6331

TABLE 3: Analysis result of experiment data.

Signal classification		Influence factors			
		Degrees of wear	Spindle speed	Feed rate	Cutting depth
AE signal	Mean 1	1.8439	1.5698	2.9001	2.4444
	Mean 2	2.2128	2.2565	2.8866	2.9852
	Mean 3	3.7796	3.1019	2.6736	2.7258
	Mean 4	3.2159	4.1239	2.5918	2.8967
	Range	1.9357	2.5541	0.3083	0.5408
Vibration signal	Mean 1	0.1894	0.5432	0.3189	0.3127
	Mean 2	0.2779	0.3784	0.2624	0.4742
	Mean 3	0.3121	0.2488	0.3947	0.3882
	Mean 4	0.7240	0.3331	0.5274	0.3283
	Range	0.5346	0.2944	0.2650	0.1615

characteristics of the analyzed signal, so that it can match the signal spectrum and improve the resolution of time-frequency, and it is widely used in engineering practice. In this paper, the wavelet packet decomposition method is used to decompose the test data, and the energy value of each frequency band signal is obtained. Then, according to the mean and range of each frequency band energy under different conditions, the relevant characteristic frequency band of acoustic emission and vibration signal is selected.

3.1. Selection of Vibration Signal Characteristics. The vibration signal of tool wear is mainly in the low-frequency band (no more than 8 kHz) [24]. Considering the integrity of the collected signal, the sensor with the frequency range of 0.7–13 kHz and sampling speed of 250 k/s is selected to collect the signal, and the db8 is selected as the wavelet base to decompose the collected signal by 6-level wavelet packet, and then the frequency difference of each frequency band is reduced to 1.95 kHz. The 6-level wavelet packet decomposition of medium wear tool vibration signal in 13–16 frequency bands is shown in Figure 5.

Since the effective frequency of the signal is not more than 13 kHz, only the first 16 of 64 bands (0~31.2 kHz) are

analyzed to avoid information redundancy. The energy changes of the first 16 frequency bands of vibration signals with different tool wear degrees are shown in Figure 6.

It can be seen from Figure 6 that the energy is mainly concentrated in P1, P2, P3, P4, P7, and P8 frequency bands. With the increase of tool wear degree, the energy increases significantly in P2, P4, P7, and P8 frequency bands. Since the effective frequency range of acceleration sensor is 0.7 Hz~13 kHz (±10%), the P8 band is omitted. The characteristic frequency bands of vibration signal are P2, P4, and P7.

Then, the mean and range of energy values in P2, P4, and P7 frequency bands under different conditions are calculated by orthogonal table to determine the characteristic frequency band which can best reflect the wear degree and is least affected by external factors. Table 4 shows the mean and range of energy values of vibration signals in P2, P4, and P7 frequency bands obtained by using orthogonal test table.

According to Table 4, the wear degree has the greatest influence on the energy changes of P2, P4, and P7 bands, which is consistent with the analysis results in Table 3.

In P2 band (1.95~3.9 kHz), the range of wear degree is 24.96, which is much larger than that of the other three
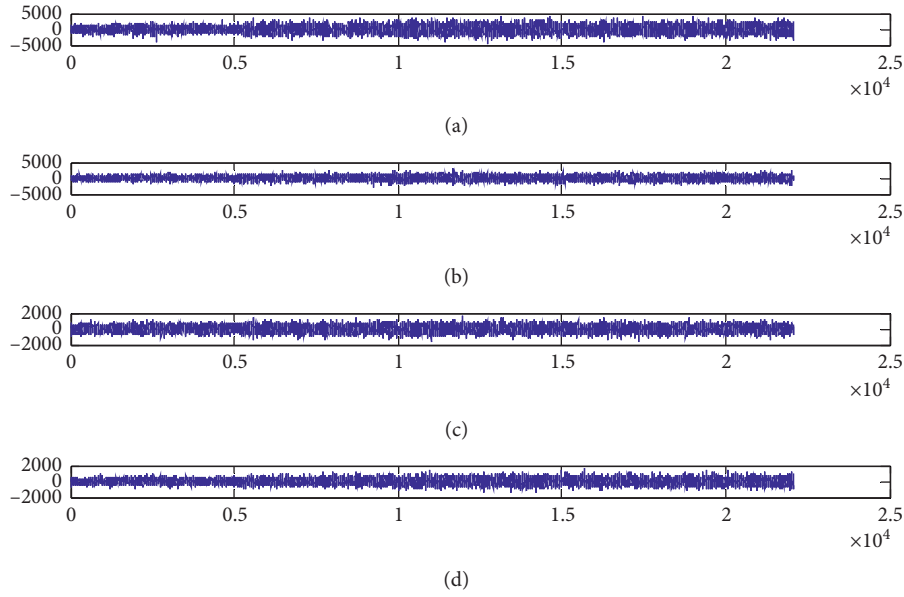
FIGURE 5: 6-level wavelet packet decomposition of medium wear tool vibration signal in 13–16 frequency bands. (a) P13. (b) P14. (c) P15. (d) P16.
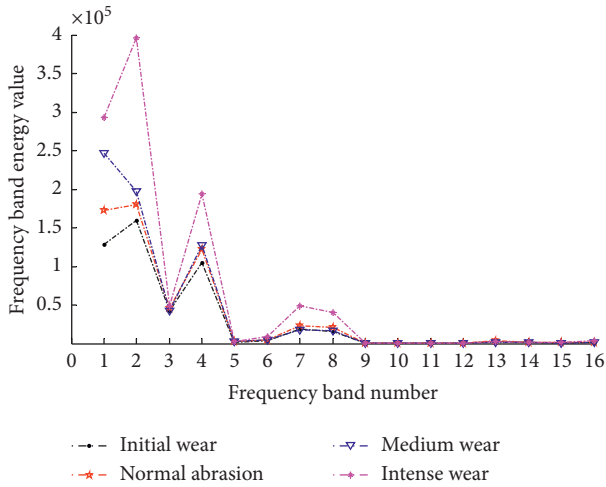

FIGURE 6: Energy value of vibration signal in different frequency bands.

factors, which are 3.35 times, 7.66 times, and 4.11 times that of spindle speed, feed speed, and cutting depth, respectively. The P2 frequency band is the most important one, and the three factors of cutting cannot be considered, so it is an ideal characteristic frequency band.

In P4 band (5.85~7.8 kHz), the range of wear degree is 41.88, which is 2.18 times, 3.23 times, and 3.70 times that of the range of spindle speed, feed speed, and cutting depth, respectively. In the P4 frequency band, the wear degree has the greatest influence on the energy change, but the influence of the three cutting factors on the energy change is relatively small, so P4 can be selected as the characteristic frequency band.

The range of wear degree in P7 band (11.7~13.65 kHz) is 18.59, which is 1.27 times, 1.44 times, and 2.02 times that of spindle speed, feed speed, and cutting depth, respectively. P7 band cannot be used as characteristic band.

Therefore, P2 is the best characteristic band of vibration signal, followed by P4.

3.2. Feature Selection of AE Signal. The acoustic emission signal of tool wear is an ultra-high frequency stress wave pulse signal with a frequency of more than 100 kHz released when dislocation, crack propagation, and plastic deformation occur in the molecular lattice during metal processing [25]. This paper selects 100 kHz~1 MHz sensor, with a sampling frequency of 2 m/s, adopts 5-stage wavelet packet decomposition, and selects dB8 as wavelet base to reduce the frequency difference of each frequency band to 31.25 kHz. The wavelet packet decomposition of AE signal shows that the energy mainly exists in P1~P16 bands (0~500 kHz), and there is almost no energy in P17~P32 bands, so only P1~P16 bands are analyzed. The energy changes of the first 16 bands of acoustic emission signals with different wear degree of the tool are shown in Figure 7.

It can be seen from Figure 7 that the energy is mainly concentrated in P1~P8 and P13 frequency bands. With the increase of tool wear degree, the energy increases significantly in P1, P2, P4, P7, and P13 frequency bands. Since the effective frequency band of AE signal is greater than 100 kHz, P1 and P2 frequency bands (0~62.5 kHz) are omitted. The characteristic frequency bands of AE signal are P4, P7, and P13.

Then, the mean and range of energy values in P4, P7, and P13 frequency bands under different conditions are calculated by orthogonal table to determine the characteristic

TABLE 4: Energy analysis results of P2, P4, and P7 frequency bands of vibration signal ($\times 10^5$).

| Frequency band	Mean and range	Experimental factors			
		Degrees of wear	Spindle speed	Feed rate	Cutting depth
P2	Mean 1	6.97	21.07	14.97	12.47
	Mean 2	11.97	13.63	15.46	18.54
	Mean 3	12.09	13.84	14.64	16.45
	Mean 4	31.93	14.43	17.9	15.51
	Range	24.96	7.44	3.26	6.07
P4	Mean 1	7.66	33.08	18.14	20.67
	Mean 2	13.38	22.83	15.84	28.32
	Mean 3	16.33	13.84	24.12	20.92
	Mean 4	49.54	17.16	28.82	17.00
	Range	41.88	19.24	12.98	11.32
P7	Mean 1	6.46	22.54	10.29	10.15
	Mean 2	10.28	11.91	8.42	19.37
	Mean 3	11.36	7.92	13.15	12.07
	Mean 4	25.05	10.77	21.29	11.55
	Range	18.59	14.62	12.87	9.22
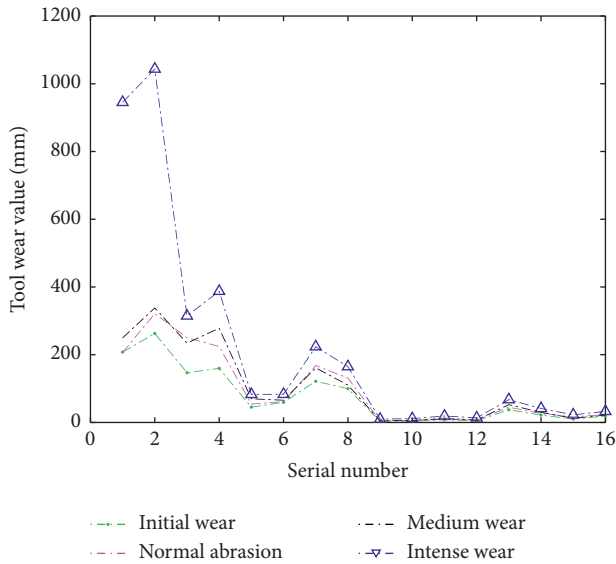
FIGURE 7: Energy value of AE signal in different frequency bands.

frequency band which can best reflect the wear degree and is least affected by external factors. Table 5 shows the mean value and range of energy value of vibration signal P4, P7, and P13 under different conditions.

It can be seen from Table 5 that the spindle speed has the greatest influence on the energy change of P4, P7, and P13 bands, which is consistent with the analysis results in Table 3.

In P4 frequency band (93.75~125 kHz), the range of spindle speed is 1432.7, the influence of tool wear degree is second only to spindle speed (range is 1116.6), and the influence of feed speed and cutting depth is relatively small (range is 568.6 and 692, respectively).

In P7 frequency band (187.5 ~ 218.75 kHz) and P13 frequency band (375~406.25 kHz), the influence of wear degree is the second, but the influence of wear degree is

similar to that of feed speed and cutting depth, so it is not suitable to be used as characteristic frequency band.

Therefore, it is more suitable to select P4 band as the characteristic band of AE signal in tool wear detection. At the same time, considering that the acoustic emission signal characteristics in tool wear monitoring system are greatly affected by the spindle speed, in order to reduce the error rate of intelligent recognition, the spindle speed is also selected as the characteristic value of AE signal.

In view of the small influence of cutting depth and feed speed on vibration and acoustic emission signals, the short-term experimental processing was carried out on the obtained worn blade samples by keeping the cutting depth and feed speed at the constant value and selecting the spindle speed randomly according to the orthogonal test speed. The acoustic emission and vibration signals of each blade during processing were collected, and the energy values of P2 and P4 frequency bands of vibration signals, the energy values of P4 frequency band of acoustic emission signals, and the corresponding spindle speed are extracted as the required characteristic parameters for the training and verification of the intelligent recognition model of tool wear state. The test parameters of this short-term experimental processing are as follows: cutting depth ap is 0.6 mm, feed speed vf is 30 mm/min, spindle speed random, using cutting fluid, processing material 45# steel bar, and each blade test time is 30 s.

4. Information Fusion Model Based on BP Neural Network

The cutting process is a complex nonlinear stochastic process with many variables. The relationship between the tool wear state and the monitored signal is also highly nonlinear. Artificial intelligence algorithms such as support vector machine (SVM), fuzzy clustering analysis (FCA), and neural network (NN) are widely used in tool wear condition

TABLE 5: Energy analysis results of P4, P7, and P13 frequency bands of AE signal.

Frequency band	Mean and range	Experimental factors			
		Degrees of wear	Spindle speed	Feed rate	Cutting depth
P4	Mean 1	1051.9	732.2	1821.5	1281.7
	Mean 2	1182.8	1159.8	1607.2	1754.3
	Mean 3	2157.1	2007.4	1306.6	1062.3
	Mean 4	1116.6	2164.9	1252.9	1618.9
	Range	1105.2	1432.7	568.6	692
P7	Mean 1	372.3	138.6	439.5	376.7
	Mean 2	331.4	250.9	499	432.3
	Mean 3	484.3	493.7	397	434.1
	Mean 4	489.3	794.1	341.7	434.2
	Range	157.9	655.5	157.3	57.5
P13	Mean 1	309.1	117.7	383.4	316.3
	Mean 2	255.8	209.1	422.5	354.5
	Mean 3	404.1	417.1	325.7	382.1
	Mean 4	445.0	670	282.4	361.1
	Range	189.2	552.3	140.1	65.8

monitoring and recognition. Support vector machine (SVM) is a pattern recognition method based on statistical learning theory and structural risk minimization principle. It takes into account the training error and generalization ability. Support vector machine (SVM) is a pattern recognition method based on statistical learning theory and structural risk minimization principle and taking into account the training error and generalization ability. SVM is widely used in pattern recognition and feature extraction such as small sample, high dimension, nonlinear, and local minimum. Fuzzy clustering analysis is an analysis method that establishes the fuzzy similarity relationship according to the characteristics, intimacy, and similarity of objective things based on the fuzzy mathematics and then classifies and identifies the fuzzy state of samples according to a certain membership degree, so as to cluster objective things. Fuzzy clustering analysis method is widely used in meteorological forecast, geology, agriculture, forestry monitoring, and other aspects. It is widely used in meteorological forecast, geology, agriculture, forestry monitoring, and other aspects. Artificial neural network is a nonlinear and adaptive information processing system composed of a large number of interconnected processing units. It can imitate the information processing function of human brain neural system in different degrees and levels. Artificial neural network is a nonlinear and adaptive information processing system composed of a large number of interconnected processing units, which can imitate the information processing function of the human brain neural system in different degrees and levels and also can provide high accuracy automatic classification ability for signals with large amount of data and complex characteristics. Artificial neural network is mainly used in the field of information processing and pattern recognition. It is mainly used in the field of information processing and pattern recognition.

In the information fusion pattern recognition system, the information provided by each information source has certain uncertainty. Choosing the appropriate fusion algorithm is the core problem of the information fusion pattern recognition system. The process of fusion of information with uncertain features is essentially an uncertain reasoning process. Neural network has strong fault tolerance, self-learning, self-organization, and self-adaptive ability, can simulate complex nonlinear mapping, and can determine the classification standard according to the similarity of the samples accepted by the current system. The characteristics of neural network and its powerful nonlinear processing ability can meet the technical requirements of multi-sensor information fusion. In view of this, this paper uses BP neural network technology to study the intelligent recognition method of tool wear state.

4.1. Structure Parameter Design of BP Neural Network

4.1.1. Design of Input Layer and Output Layer. The energy values of P2 and P4 frequency bands of vibration signal, P4 frequency band of AE signal, and corresponding spindle speed are selected as the four main characteristic parameters of tool wear. Therefore, the input vector is determined to be 4, that is, the number of neurons in the input layer is 4. The output is the tool wear, so the number of neurons in the output layer is 1.

4.1.2. Hidden Layer Design. According to Kolmogorov theorem, a three-layer BP neural network can realize the nonlinear mapping from any n dimension to m dimension. In this paper, a single hidden layer structure is selected. The number of nodes in the hidden layer directly affects the performance of neural network. The number of nodes is too small, and the pattern space is rough, which leads to poor fault tolerance and low ability of identifying the samples without learning. Too many nodes and too fine division of pattern space lead to too long network training time, slow or even nonconvergence of the network, and storage of the irregular content in the sample, reducing the generalization ability of the system. The number of hidden layer nodes is [26]

$$l = \sqrt{n + m + a}, \tag{1}$$

where l is the number of hidden layer nodes, n is the number of input nodes, m is the number of output nodes, and a is the adjustment constant between 1 and 10.

The BP neural network model is established among 4–15 hidden layer neurons by the trial method, and the optimal number of hidden layer neurons is determined by network error. When the number of hidden layer neurons is 9, the network error is the smallest, and the number of hidden layer nodes is 9. Therefore, the 3-layer BP neural network structure based on the intelligent recognition of tool wear state based on information fusion is 4-9-1. According to the output of BP neural network, the wear degree of the tool can be directly determined.

4.2. Multi-Information Fusion Based on BP Neural Network. The physical quantities of vibration signal, acoustic emission signal, and spindle speed characteristic parameters have different meanings. Before neural network training, the characteristic data should be normalized. The normalization method was used.

$$x_i^0 = 1 - \frac{|x_i - \overline{x}|}{(x_{\max} - x_{\min})}. \qquad (2)$$

Among them, $x_{\max} = \max\{x_i\}, x_{\min} = \{x_i\}, \overline{x} = \sum_{i=1}^{n} x_i/n$.

So, the values of the input vectors are all between 0 and 1.

The hyperbolic tangent function is chosen as the activation function [27]. The initial weight of the network is randomly selected between (0, 1). The learning rate is 0.01, the training error is 1×10^{-8}, and the maximum training period is 40000. From the test characteristic data, 16 groups of P2 and P4 band energy value of the vibration signal and P4 band energy value of the acoustic emission signal are selected randomly, and the corresponding spindle speed also is selected together as the training samples to train the BP neural network. The 3-layer BP neural network model with 4-9-1 network structure is trained, and the training target precision is achieved through 31 steps. The training error curve is shown in Figure 8.

5. Test Results and Analysis

18 groups of P2 and P4 band energy value of the vibration signal and P4 band energy value of the acoustic emission signal which are not the training samples are selected from the test characteristic data, and the corresponding spindle speed also is selected as the test samples together. These test samples are input into the BP neural network to verify the intelligent recognition method of tool wear state.

Firstly, the pattern recognition method of support vector machine is used to recognize the tool wear state based on single sensor information. Then, BP neural network technology is used to identify the tool wear state by fusing the vibration signal, acoustic emission signal, and spindle speed feature information. Finally, the above discrimination results were compared with the actual detection results of tool wear (18 samples, including 1 initial
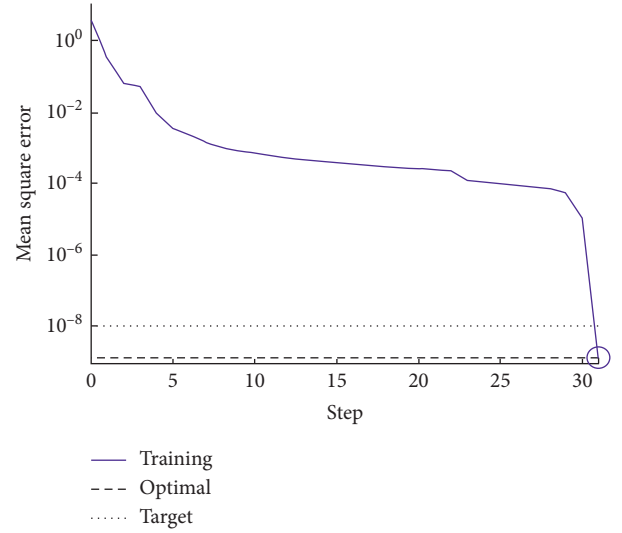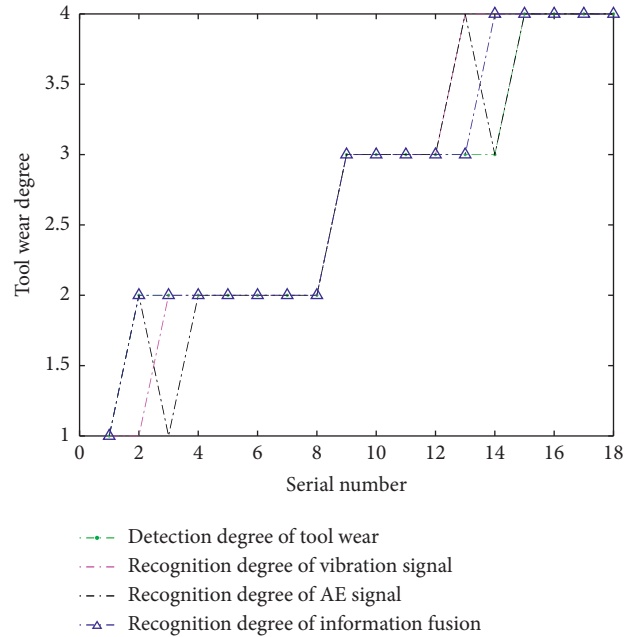

FIGURE 8: Training error curve.

FIGURE 9: Tool wear detection and recognition degree.

wear, 7 types of normal wear, 6 types of moderate wear, and 4 types of severe wear).

The 18 samples were sorted according to the actual value of tool wear. The actual detection degree of tool wear, the recognition degrees by single vibration signal or single acoustic emission signal, and the recognition degree by information fusion are shown in Figure 9.

The results of single vibration signal identification were as follows: one normal wear (No. 1) was misjudged as initial wear, and two kinds of moderate wear (Nos. 13 and 14) were misjudged as severe wear. The recognition accuracy of all samples was 83.33%. The results of single acoustic signal recognition were as follows: 1 normal wear (No. 3) was misjudged as initial wear, 1 medium wear (No. 13) was
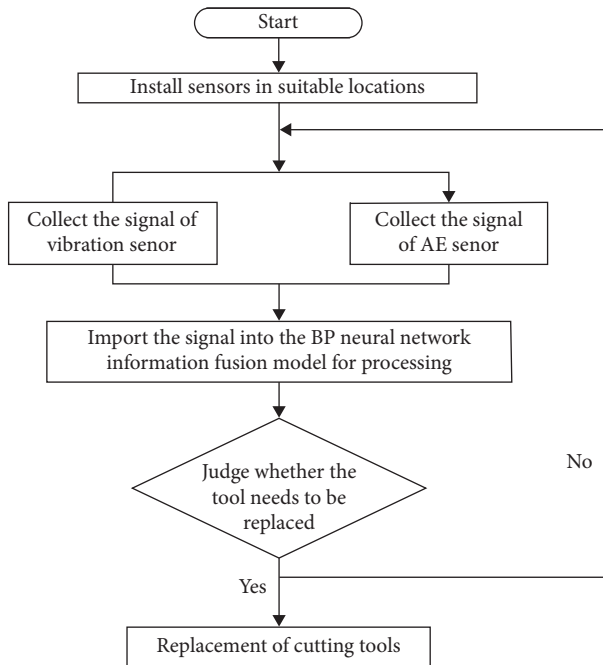
FIGURE 10: Diagnosis flowchart of tool wear status.

misjudged as severe wear, and the accuracy rate of identification for all samples was 88.89%. The result of information fusion identification was as follows: one medium wear (No. 14) was misjudged as severe wear, and the accuracy of all samples was 94.44%.

The accuracy of tool wear state recognition based on neural network multi-information fusion is 11.11% and 5.55% higher than that based on vibration signal and acoustic emission signal.

The diagnosis flowchart of the tool wear status is shown in Figure 10.

6. Concluding Remarks

Tool wear state directly affects the accuracy, efficiency, and cost of workpiece processing and the stability of the whole manufacturing equipment system.

(1) This paper studies the application of information fusion technology in tool wear state recognition. The multi-information data acquisition system of tool wear condition of CNC lathe is composed of a CNC lathe, workpiece, sensor, and signal amplifier and also includes a data acquisition, analysis, and processing device.

(2) In this paper, BP neural network is used to fuse the feature information of vibration signal and AE signal with high correlation with tool wear degree, a 3-layer BP neural network tool wear state intelligent recognition model with 4-9-1 structure is constructed, and the model is trained.

(3) The experimental results show that the recognition accuracy of the intelligent recognition system for tool wear state of CNC turning tool in all experimental samples is 94.44%, which is 11.11% higher than that of vibration sensor and 5.55% higher than that of AE sensor.

The accuracy of the tool wear state identified by the information fusion method is higher than that of the tool wear state identified by a single sensor, which effectively realizes the monitoring and automatic monitoring of the tool wear state and has a certain practical application value. However, the model established in this paper is only suitable for CNC lathe and has low universality.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

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