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연삭가공의 이상상태 진단 기법

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Trouble Diagnostic Method in Grinding Process

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Abstract

A chatter vibration and a workpiece burn are the main phenomena to be monitored in modern grinding processes. This study describes a trouble diagnosis of the cylindrical plunge grinding process using the power and acoustic emission (AE) signals. The raw signals of the power and the AE occurred during the grinding operation were sampled and analyzed to determine the relationship between each fault and change of signals. A neural network that has a high success rate of the fault detection was used. Furthermore, an analysis on the influence of parameters to the chatter vibration and the grinding burn was conducted.

Keyword : Cylindrical plunge grinding process(원통 플런지 연삭가공), Power signals(동력신호), Acoustic emission(음향방출), Neural network(신경회로망)

1. Introduction

The development of automatic systems is the ultimate goal of a grinding research. One of the most important automatic techniques that should be developed at the current stage is an on-line fault diagnosis system. The grinding operation has been used in machining the precision products that cannot be met for the surface roughness and the geometric tolerances with the traditional cutting operations. However, there are unique characteristics of the grinding processes in the tools used, the cutting conditions, and the machining mechanism. For this reason, the grinding process includes many functional parameters and the qualitative interactions between these parameters cannot be understood [1, 2]. The grinding burn is one of the fault phenomena happened to the ground surface. It is related to the thickness of an oxide layer, which is affected by the maximum temperature at the cutting zone [3]. This layer for a ferrous material is composed of Fe_2O_3, Fe_3O_4, and FeO membranes from the free surface. Another trouble is a chatter vibration that is relative motion between the grinding wheel and the workpiece. The increased grinding force associated with the chatter vibration leads to accelerate the wheel wear [4]. Chatter marks normal to the grinding direction can be seen on the ground surface. Therefore, it is important to detect these faults during the machining processes.

This study presents a neural-network-based fault diagnosis scheme, which monitors the chatter vibration and the burning phenomena in the cylindrical plunge grinding operations. The scheme utilizes the signal components of the power and the AE as the input to the neural network. In power signal, four parameters, such as the static power, the dynamic power, the power variation, and the settling time, are extracted from the acquired power raw signals. The relationship between the parameters, such as the learning rates and the momentum coefficients, and the fault recognition is also discussed.

2. Learning theory of the neural networks

As mentioned previously, the grinding process has the nonlinear characteristics. This non-linearity fails to understand completely the grinding operation with a conventional analytic approach and extorts other scheme from many researchers.

Artificial neural networks have been studied for many years in the hope of achieving the human-like performance in the field of the speech, the image recognition and the pattern classification. These neural networks are composed of many non-linear computational elements operating in parallel. Neural networks, because of their massive nature, can perform computations at a higher rate. Because of their adaptive nature using the learning process, neural networks can adapt to changes in the data and learn the characteristics of the input signals.

Learning in a neural network means the finding an appropriate set of the weights that are connection strengths from the elements to the other layer elements. In this study, the back propagation algorithm of neural networks that is one of the various learning modes is used. The squared error (E_p) and the weight-change equation on the output layer are simply given by following relations [5].

$$E_p = \frac{1}{2}\sum_k (T_{pk} - O_{pk})^2 \tag{1}$$

$$\frac{\partial E_p}{\partial W_{ji}} = \frac{1}{2}\sum_k \frac{\partial}{\partial W_{ji}}(T_{pk} - O_{pk})^2 = -\sum_k (T_{pk} - O_{pk}) f_k'(net_{pk}) W_{kj} f_j'(net_{pj}) X_{pi} \tag{2}$$

$$W_{kj}(t+1) = W_{kj}(t) + \alpha\delta_{pk} i_{pj} + m\Delta W_{kj}(t-1) \tag{3}$$

where W_{ji} is the weight on the connection from the ith input element, α is called the learning-rate parameter. The i_{pj} and the δ_{pk} can be presented as followings:

$$i_{pj} = \left(\frac{\partial}{\partial W_{kj}}\sum_{j=1}^{L} W_{kj} X_{pj} + \theta_k\right) \tag{4}$$

$$\delta_{pk} = T_{pk} - O_{pk} \tag{5}$$

m is an output data of the neural networks. X_{pj} is a teaching data and $f'()$ means a derivative of the sigmoid transfer function for each layer. T_{pk} is an input pattern and O_{pk} is the momentum coefficient that increases the speed of the convergence for learning the neural networks.

3. Experimentation and results

3.1 Experimental method

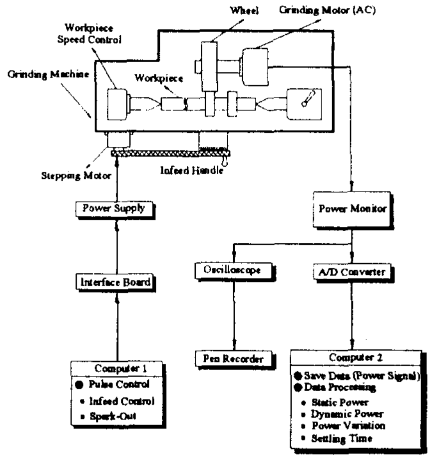


Fig. 1 Experimental setup for acquiring the power signals.

A scheme of the experimental setup for acquisition of the power signals is shown in Figure 1. A series of grinding tests were conducted on a cylindrical grinder with a 228 mm diameter WA60LmV wheel that is mostly occupied with a general purpose in workshop. Specimens STD11 that is preferred to the die and the mold materials were tested. A power monitor with 10 kHz sampling frequency was used to measure the signal changes during the grinding operation. An oscilloscope visualized the power signals obtained and a pen recorder plotted the signals. Signals outrunning the power monitor were converted analog to digital. Digitalized signals stored in a personal computer. The stored signals were analyzed through the data processing.

For obtaining the AE signals, an AE sensor with a frequency response of wide bands (100~800 kHz) was used to measure the signals generated during the grinding operation. The sensor was attached to the death center of a grinding machine. To avoid signal attenuation during the transportation from the sensor to a computer, a pre-amplifier was connected to the cable of signal flow and its auxiliary function was to filter the noise that disturbs the AE signals. The raw AE signals were digitized using an A/D converter.

Grinding conditions used in monitoring the power and the AE signals are listed in Table 1.

Table 1 Grinding conditions.

Items	Conditions
Grinding Wheel	Type : WA60LmV
	Size : ϕ228 × 24
Wheel Speed	V_s = 27.1 m/s (1800 RPM)
Workpiece	Material : STD11
	Hardness : H_RC 45
Workpiece Speed	V_w = 0.20 ~ 0.40 m/s
Infeed Rate	0.5 mm/min
	1.0 mm/min
	2.0 mm/min
Cutting Fluid	Dry Cut
Dressing	Depth of Cut : 0.015 mm
	Lead : 0.020 mm/rev

3.2 Experimental results and discussion

3.2.1 Power signals

Figure 2 shows the typical form of the power signals obtained during the grinding operation. In the general case as shown in Figure 2(a), the grinding power increases rapidly with the contact between the grinding wheel and the workpiece.

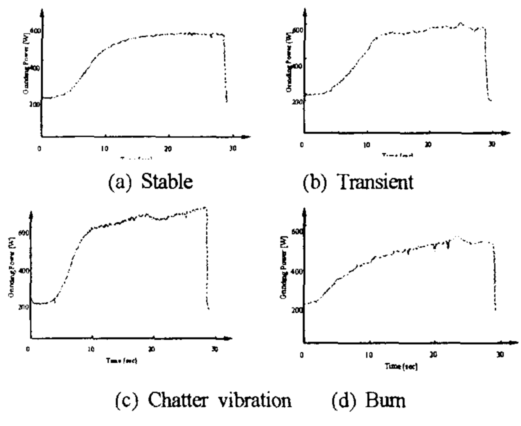


Fig. 2 Obtained power signals.

This time is an initiative point of the grinding. After several times, this grinding power settles down a certain level of the amplitude that is the static power. According to the continuous machining operation, the grinding power maintains mostly its level. When separation between the grinding wheel and the workpiece is progressed, the grinding power has seriously a reduction of its level. These changes of the grinding power compose the grinding cycle.

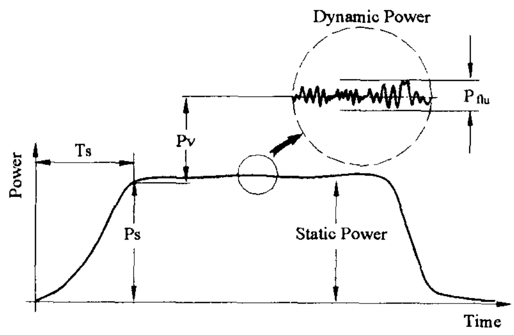
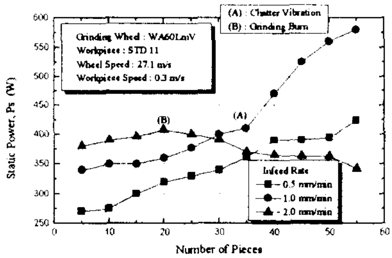


Fig. 3 The used parameters for the power signals.

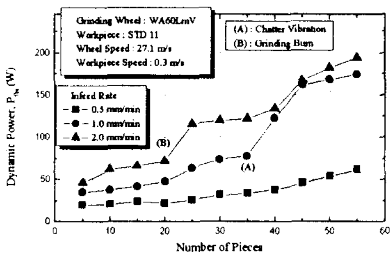
Normally, the static power remains with a constant magnitude, but many times happen to change its level. For the occasion of the chatter vibration and the burn shown in Figure 2(c) and (d), the static powers have a magnitude significantly different than the aspects as shown in Figure 2(a) and (b).

Therefore, grinding states can be predicted with monitoring the power signals. To forecast the grinding states, the parameters of the power signals must be determined. Shown in Figure 3, these parameters are Ts, Ps, P_{flu}, and Pv. Ts is a settling time that is composed of a starting point with a slope of 30° and a final point with a slope of 5° to the horizontal line. A sampled mean power divided by the machining time is defined as the slopes. Static power Ps is the magnitude from the starting point to the ending point according to the vertical axis and presents an absolute level of the power generated in the grinding zone. Dynamic power P_{flu} is a power component of the high frequency and it fluctuates around the static power level. In the calculation of the dynamic power, it was defined as difference between the maximum power and the minimum power within the twenty sampled data on the mid-point of a total grinding time. Finally, power variation Pv is a difference between the static power and a mean value of the dynamic power on the mid-point of the total grinding time.

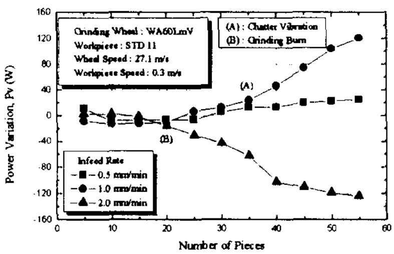
Figure 4(a) shows the static power characteristics according to the number of the grinding pieces. When the in-feed rate is 0.5 mm/min, the static power increases gradually in stable state of the machining process. On the other hand, the static power with the in-feed rate of 1.0 mm/min ascends



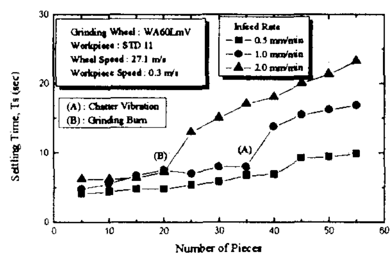
(a) Static power



(b) Dynamic power



(c) Power variation



(d) Settling time

Fig. 4 Characteristics of the parameters according to the number of the grinding pieces.

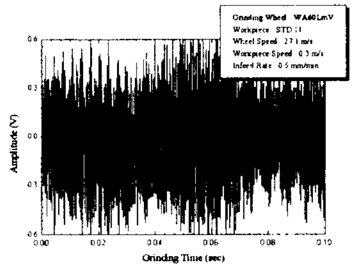
excessively to generate the chatter vibration pointed to (A). In opposition to the chatter vibration, the static power decreases evidently with the generation of the workpiece burn pointed to (B). Dynamic power characteristics are shown in Figure 4(b). Dynamic power increases dramatically in the generation of not only the chatter vibration but also the workpiece burn.

Figure 4(c) shows the power variation according to the number of the grinding pieces. The interesting results with respect to the power variation were obtained. The power variation of the stable state is nearly a constant but diverges from a rise and a drop with the chatter vibration and the workpiece burn respectively. These behaviors of the power variation are important characteristics for monitoring the grinding states. A drop of power variation is due to the wheel loading that is the situation of not machining the materials with the adhesion of the removed chips in the wheel void.

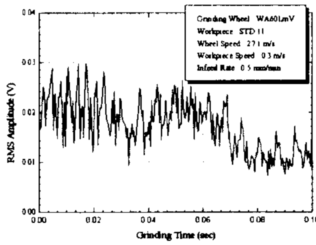
Figure 4(d) shows the settling time characteristics according to the number of the grinding pieces. The settling times were increased when the chatter vibration or the workpiece burn are generated.

3.2.2 AE signals

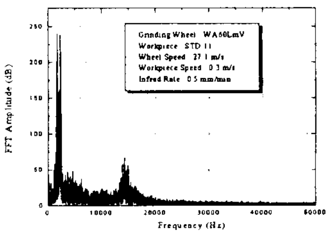
Figure 5(a) shows typical AE signals obtained from the grinding operation. As other metal cutting processes, the raw signals are continuous types and sharply fluctuate with grinding time. The amplitudes of raw signals increase according to the number of ground workpieces, but because of the similitude in signals grinding states are not always distinguished either stable or unstable. Therefore, other analytic parameters are needed to identify the grinding state. Figure 5(b) presents the signal to process the RMS with the raw signal shown in Figure 5(a). The changes in AE signals are easily verified by an AE RMS level and a distinctive type. The results of the frequency analysis with the raw signals are drawn in Figure 5(c). The FFT amplitude is evident, especially when the frequency ranges reach about 1.8 kHz and 15 kHz. Because the wheel rotational frequency is approximately 30 Hz, it can be seen that a trouble frequency is an integer multiple of the wheel



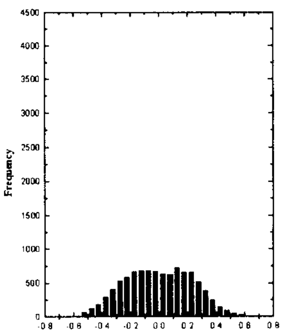
(a) Raw signal



(b) RMS signal

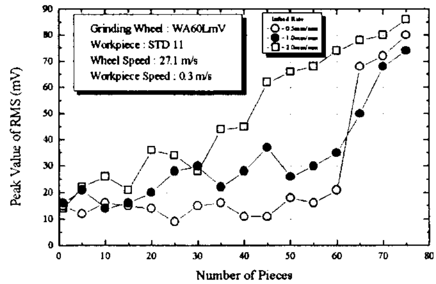


(c) FFT signal

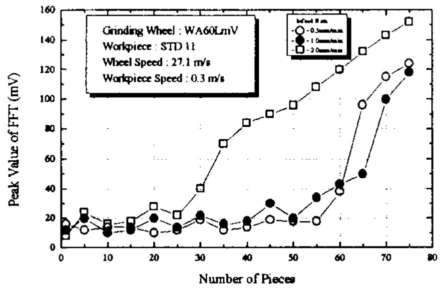


(d) Distribution

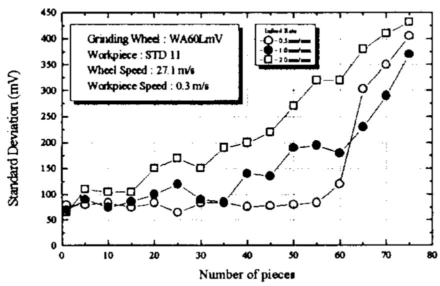
Fig. 5 AE signal and signal processed forms.



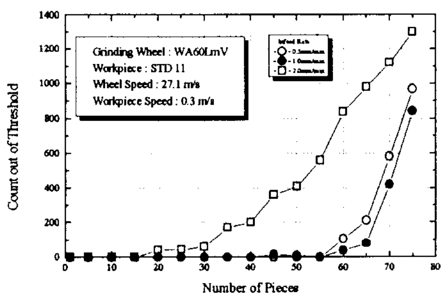
(a) RMS variation



(b) FFT variation



(c) Standard deviation



(d) Count out of threshold

Fig. 6 Change of AE parameters.

rotational frequency. When the sampled values have a sufficiently strong central tendency, then a standard deviation of the sampled values may be useful for characterizing the set. The standard deviation is the positive square root of the variance that reveals the degree of distribution for the sampled data. Figure

5(d) presents the distribution of AE signals, and it shows that the stronger central tendency is in a stable grinding state. Based on the above results, the parameters of the AE signals for monitoring troubles have been selected, measured, and are shown in Figures 6.

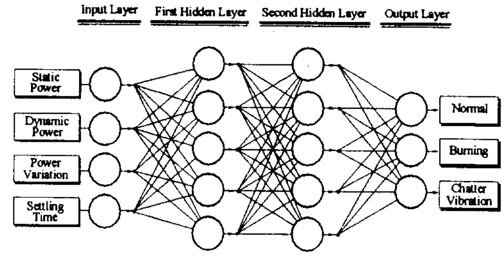
In Figure 6(a), the peak values of RMS increase gradually according to the number of grinding pieces. It was found that the more the in-feed rates are applied, the higher the level of the RMS peak became. Figure 6(b) presents the peak values of FFT. The FFTs level maintains to a particular piece, as an example, the 25th piece with 2.0 mm/min in-feed rate, and after the 25th piece, the peak level increases suddenly. The boundary point of the peak values reveals the generated trouble. In this case, the trouble is chatter vibration.

Figure 6(c) presents the standard deviation of the raw AE signals according to the number of grinding pieces. It can be seen that the value of the standard deviation increases when the number of ground pieces increases. Figure 6(d) shows the count outs of the threshold over the 20 mV level of the acquired raw signal that was enumerated with a computer program. The threshold level is determined by a preliminary experiment. The increased count out of the threshold may be considered as a sign of a trouble. By varying the parameters, a more effective diagnosis system for grinding troubles can be established.

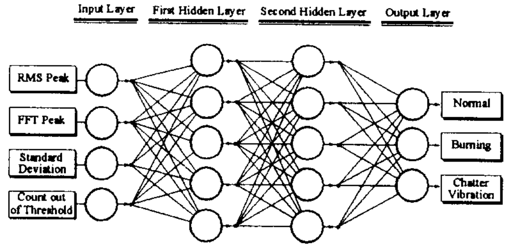
4. Evaluation of the diagnostic system

According to the selection of above parameters, especially the learning-rate and the momentum coefficient, the performance of neural networks is widely different from the others under the same condition. Therefore, it is necessary to optimize the neural network with the correct parameters. From the preliminary study, the learning-rate and the momentum coefficient were determined to the values of 0.6 and 0.8 respectively. In addition, the number of the hidden layers was selected as two.

The trouble recognition of the grinding process was conducted on a personal computer. Figure 7 presents the architecture of the neural network used in this study. As shown in Figure 7(a), Input units of the power diagnostic system were used the settling time, the static power, the dynamic power, and the power variation of the acquired signals. Variables of the normal, the burning, and the chatter vibration states were occupied for the output parameters that had the interval values from 0 to 1. In comparison with these values of the output parameters, the parameter with the major value means the states of the grinding operation being. Figure 7(b) presents the architecture of the AE diagnostic system.



(a) Power diagnostic system



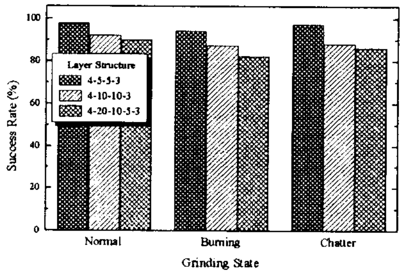
(b) AE diagnostic system

Fig. 7 Architecture of the neural networks.

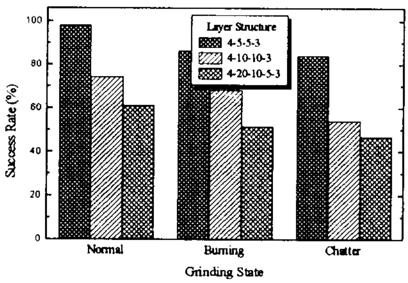
Table 2 Clustering the power parameters.

Parameters	Low : 1	Middle : 2	High : 3
P_s	Below 370 (W)	370~420 (W)	Over 420 (W)
P_{flu}	Below 50 (W)	50~80 (W)	Over 80 (W)
P_v	Below -20 (W)	-20~20 (W)	Over 20 (W)
T_s	Below 6 (sec)	6~12 (sec)	Over 12 (sec)

During the learning process of the neural network, the power diagnostic system failed to converge the squared error. In order to reduce the squared error, it is



(a) Power diagnostic system



(b) AE diagnostic system

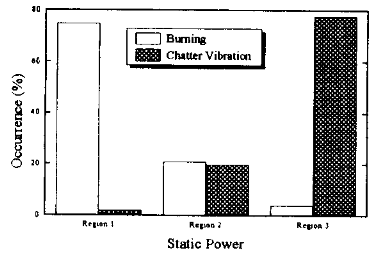
Fig. 8 Performances of the recognition system.

essential to cluster the range of the input parameters. With the range analysis of the acquired signals, clustering the range of the power parameters listed in Table 2 was accomplished.

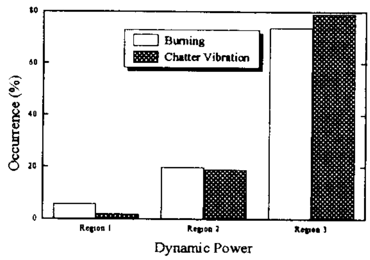
Figure 8 presents the percentages of the success rate according to the various layer structures in the established recognition system. From the Figure 8, it is evident that the maximum performance, in power diagnostic system, is about 95% when the neural network is optimized, while in AE diagnostic system about 90%. It is seen evidently that the power diagnostic system is more effective method for monitoring the grinding state.

To improve the recognizable performance, an analysis on the influence of the power parameters to the chatter vibration and the grinding burn must be conducted. Therefore, from the results of the experimentation and the simulation, the relationship between the range of each parameter and the grinding troubles was obtained. Figure 9 presents a percentage of the trouble occurrence according to a region of the power parameters.

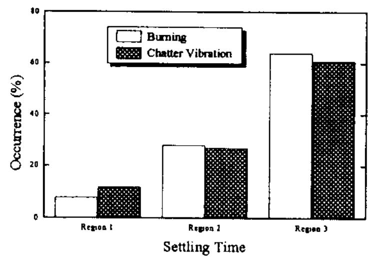
From the results as shown in Figure 9, it may be seen that the grinding burn and the chatter vibration



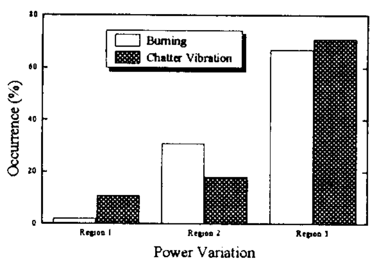
(a) Static power



(b) Dynamic power



(c) Settling time



(d) Power variation

Fig. 9 Percentage of the trouble occurrence according to the region of the parameters.

during the grinding process can be monitored effectively with detecting a change of the static power. In the occurrence of the burning, there is the static power in the region 1, while the static power is in the region 3 coinciding with the occurrence of the chatter vibration.

5. Conclusion

In order to recognize the grinding trouble involved with the chatter vibration and the workpiece burn, the experimentation on a cylindrical plunge grinder and the computer simulation was carried out. Based on these results, the conclusions can be drawn as followings:

1. To forecast the grinding state, the parameters of the power signals were determined. Static power increased gradually in the stable state. On the other hand, the static power ascended excessively or decreased when the chatter vibration and the workpiece burn were generated respectively. The power variation of the stable state was nearly a constant but diverged from a rise and a drop with the chatter vibration and the workpiece burn respectively. As a trouble happened, the other parameters increased also.
2. When grinding troubles such as chatter vibration and grinding burn occur, the values of the AE parameters for the peak of the RMS, the peak of the FFT, the standard deviation, and the count out of the threshold all increase non-linearly. The more the in-feed rates are applied, the higher the levels of AE parameters become. The FFT amplitude is especially evident when the frequency ranges reach about 1.8 kHz and 15 kHz. Because the wheel rotational frequency is approximately 30 Hz, it is seen that a trouble frequency is an integer that is a multiple of the wheel rotational frequency.
3. From the implementation results of the computer simulation for the new data that were not learned, the normal parameter has a higher concentration of unity, while others such as the burn and the chatter vibration parameters have a lower. A few erroneous recognitions were made in the boundary point between the burn and the chatter vibration. The maximum performance, in the power diagnostic system, was about 95% when the neural network was optimized.

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