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연삭 동력신호를 응용한 결함진단에 관한 연구

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A study on the Fault Diagnosis Applied to the Grinding Power Signals

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Abstract

Undesired trouble such as chatter vibration and burning on the ground surface appears frequently in the cylindrical plunge grinding process. Establishment of a credible fault diagnostic system for the grinding process is the major purpose of this study. Power signals generated during the grinding operation were sampled and analyzed to determine the relationship between grinding troubles and behavior of signal changes. In addition, a neural network that has an excellent ability for pattern classification was occupied for the trouble recognition. The neural network was optimized with a momentum coefficient, a learning rate, and a structure of the hidden layer through the iterative learning process. Based on the established system, success rates of the trouble recognition were verified.

Key Words : Fault diagnostic system, Power signals, Neural network. Grinding process

1. Introduction

Grinding operation has been used in machining the precision products that cannot be met for surface roughness and geometric tolerances with traditional cutting operations. With an increase in demand for near net shape technique in precision components, more improved grinding performance is required. However, there are unique characteristics of the grinding process. For example, as opposed to a turning tool, grinding wheels contain many grains that are randomly spaced and occupied in the periphery of the wheel. For this reason, a mathematical approach with respect to the grinding process includes many functional parameters that cannot certify their quantitative relations.[1,2]

Grinding burn is one of the troubling phenomena that happen to the ground surface. It is related to the thickness of the oxide layer, which is affected by the maximum temperature at the cutting zone.[3] The generated burn deterio-

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rates the surface performance of a product. The other trouble is a chatter vibration that is relative motion between the grinding wheel and the workpiece. As a result of this motion, the ground surface includes the undesired integrity and, in some cases, the damage. In addition, the increased grinding force associated with the chatter vibration leads to accelerate a wheel wear.[4] The investigation described in this research focuses on the development of a credible trouble detection system for the grinding process.

The power signals obtained from an induced motor of a grinding machine were analyzed to determine the relationship between grinding troubles and behavior of signal changes. Furthermore, a neural network having an excellent ability for pattern classification was applied to the trouble detection system. The neural network was optimized with a momentum coefficient, a learning rate, and a structure of the hidden layer in the iterative learning process. The success rates to verify the degree of trouble detection were evaluated with a new learning data set.

2. Troubling Phenomena in the Grinding Operation

Workpiece burn during the grinding process is essentially a kind of irreversible changes in microstructure of the surface layer taken place under the action of continuous high temperatures at the grinding zone. Visual observation of grinding burn is due to temper colors from very thin oxide layers on the workpiece surface. This layer for ferrous material is composed of, in turn, Fe_2O_3, Fe_3O_4, and FeO membranes from a free surface. At the onset of grinding burn, the grinding force and rate of wheel wear increases sharply, and the surface roughness deteriorates.

S. Malkin[5] proposed a critical limit of grinding burn with respect to various items in surface grinding. Based on his research, grinding burn appears easily on the surface of the workpiece when smaller abrasives, higher grades of the grinding wheels and more hardened materials are used. Chatter vibration is a dynamic instability of most machining processes, including grinding, and is considered to be the most serious phenomenon of surface quality. In general, it limits the productivity of the machining process and causes deterioration of the workpiece surface integrity. Moreover, in grinding, the growth of wavy surface on the grinding wheel induced by the chatter vibration results in the need for interruption of the grinding process and for dressing the wheel.

Grinding processes are often selected for the final finishing of a component because of their ability to satisfy strict requirements of surface roughness. However, in the case of grinding trouble generation, a finer allowable range of surface roughness is not maintained. The fine scale morphology of the surfaces produced by the grinding operation consists mostly of overlapping scratches generated by the interaction of abrasive cutting points with the workpiece. An example of a typical ground surface is shown in Figure 1(a). In this example of cylindrical plunge grinding, the uniform abrasive motion relative to the workpiece is readily identified from the direction of the scratches.

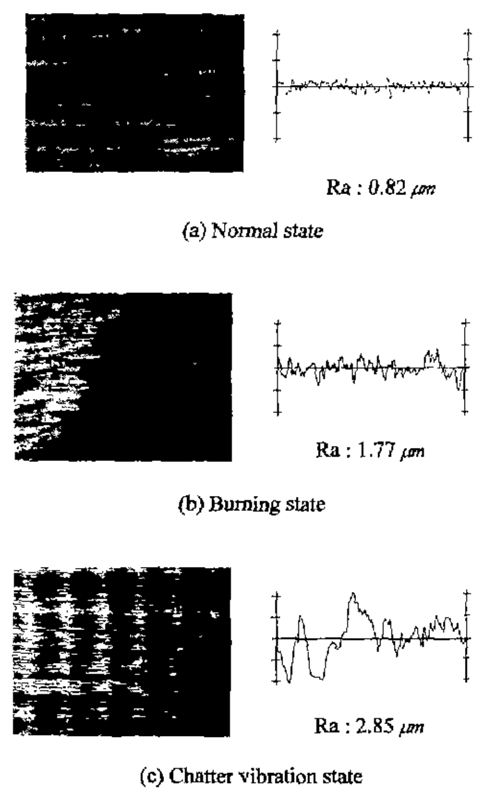


Fig. 1 Surface integrity changes in the plunge grinding

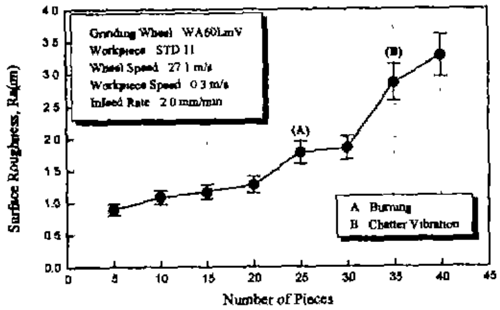


Fig. 2 Surface roughness versus number of pieces

The ground surface morphology is further complicated by other phenomena. The grinding burn of the workpiece often occurs, especially with adhesive materials. Metals adhering between voids within the grinding wheel constrict the action of machining. Therefore, the grinding operation becomes an abnormal state and the grinding temperature instantaneously rises about 1,000℃. Due to rising temperatures, the workpiece surface is burnt as shown in Figure 1(b).

Figure 1(c) shows the chatter vibration of a ground surface. At this time, the grinding process is in an unstable state. Chatter marks, which are normal to grinding direction, can be seen on the ground surface. As the grinding burn and chatter vibration take place, surface roughness deterioration is evident.

Figure 2 shows the variation of surface roughness according to the number of pieces. The values of surface roughness are slightly increased in the normal state of grinding, but rapidly increased in trouble states. In order to produce a satisfactory product, it is evident that grinding troubles, such as grinding burn and chatter vibration, must be avoided by credible methods.

3. Experimentation for Acquiring the Trouble Data

3.1 Experimental Method

A schematic experimental setup is shown in Figure3.

A series of grinding tests was conducted on a cylindrical grinder with a 228 mm diameter, WA60LmV, wheel which is commonly used in workshops. Specimens

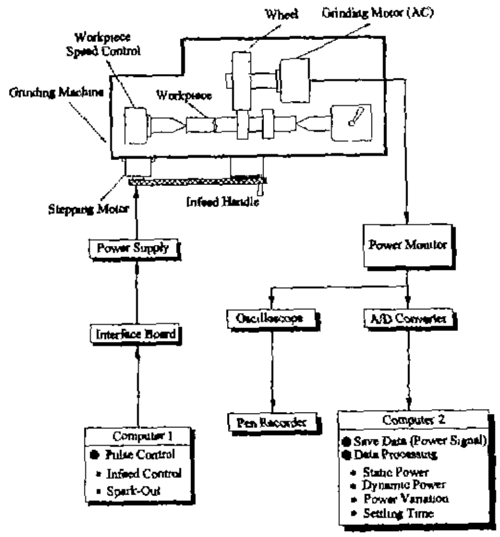


Fig. 3 Experimental setup for trouble detection system

Table 1 Grinding conditions for obtaining signals

Items	Conditions
Grinding wheel	Type . WA60LmV
	Size . φ228 * 24
Wheel speed	Vs = 27.1 m/s (1,800 rpm)
Workpiece	Material : STD11 (H_RC 45)
Workpiece speed	Vw = 0.15~0.30 m/s
Infeed rate	0.5~2.0 mm/min
Dressing condition	Single point diamond dresser Depth of cut : 0.0125 mm Lead · 0.015 mm/rev

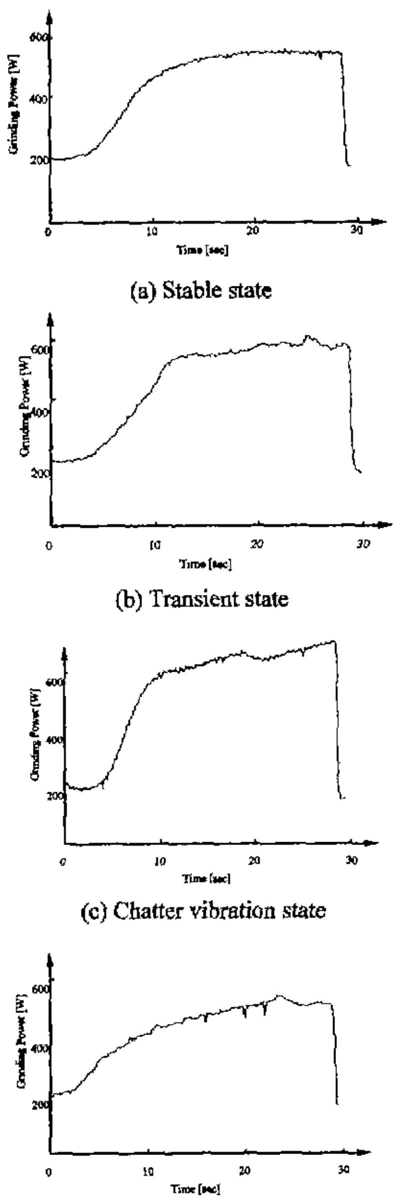
STD11, which are preferred to the die and the mold materials, were tested. A power monitor with a 10 kHz sampling frequency was used to measure the signal changes during the grinding operation. Oscilloscope visualized the power signals obtained and pen recorder plotted. Signals outrunning the power monitor were converted from analog to digital. Digitalized signals were stored in a personal computer. Stored signals were analyzed through the data processing. Grinding conditions used in monitoring the power signals are listed in Table 1.

3.2 Experimental results and discussion

Figure 4 shows the typical form of power signals obtained during the grinding operation. In the general case shown in Figure 4(a), grinding power increases rapidly with contact between the grinding wheel and the workpiece. This time is the initiative point of grinding. After several seconds of this point, the grinding power settles down at a certain level of amplitude that is static power. According to continuous machining operation, the grinding power mostly maintains its level. When separation between the grinding wheel and the workpiece is progressed, the grinding power is suddenly reduced. These changes of grinding power compose the grinding cycle.[6]

Normally, static power remains with a constant magnitude, but happens to change its level. According to chatter vibration and burning as shown in Figure 4(c) and (d), static powers have a magnitude significantly different than the aspects shown in Figure 4(a) and (b). Therefore, the grinding states can be predicted by monitoring the power signals. To forecast the grinding states, the parameters of power signals are determined.

As shown in Figure 5, these parameters are Ts, Ps, P_{flu}, and Pv. Ts is the 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. The sampled mean power divided by machining time is defined as the slopes. Static power Ps is the magnitude from the starting point to the ending point according to a vertical axis and presents an absolute level of power generated in the grinding zone. Dynamic power P_{flu} is a power component of high frequency and it fluctuates around the static power level. In the calculation of dynamic power, it was defined as the difference between maximum power and minimum power within twenty sampled data on the mid-point of total grinding times. Finally, power varia-



(a) Stable state

(b) Transient state

(c) Chatter vibration state

(d) Burning state

Fig. 4 Power signals obtained in the grinding process

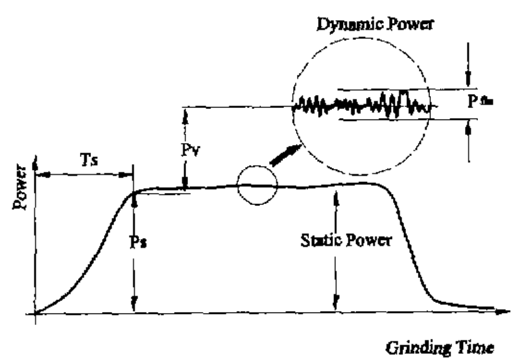


Fig. 5 Definition of the used parameters for power signals

tion Pv is the difference of power between static power and mean value of dynamic power on the mid-point of the total grinding time.

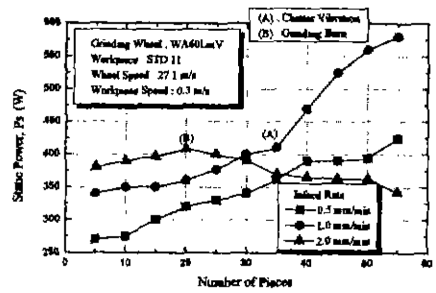
Figure 6(a) shows static power characteristics according to the number of grinding pieces. When the in-feed rate is 0.5 mm/min, static power increases gradually in a stable state of the machining process. On the other hand, static power with an in-feed rate of 1.0 mm/mm ascends excessively to generate a chatter vibration pointed to (A). In opposition to the chatter vibration, the static power decreases evidently with the generation of workpiece burning pointed to (B). Dynamic power characteristics are shown in Figure 6(b). Dynamic power increases dramatically in generation of not only chatter vibration but also workpiece burning.

Figure 6(c) shows the power variation according to the number of grinding pieces. Interesting results with respect to power variation were obtained. The power variation of stable state is nearly constant but diverges from a rise and a drop with the chatter vibration and workpiece burning respectively. These behaviors of power variation are important characteristics for monitoring the grinding state. A drop in power variation is due to the loading that make wheel disable to cut the materials because of an adhesion of removed chips in the wheel void. Figure 6(d) shows the settling time characteristics according to the number of grinding pieces. Settling times were increased when the chatter vibration or the workpiece burning were generated.

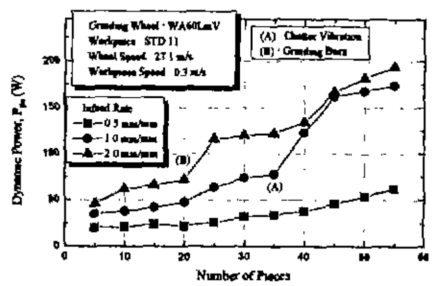
4. Development of Fault Diagnosis System

4.1 Learning Theory of the Neural Networks

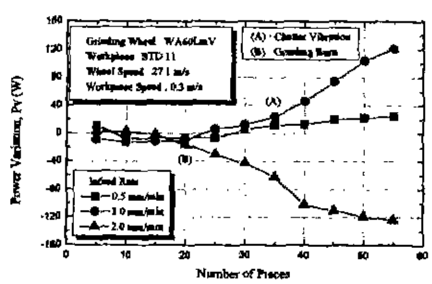
Artificial neural networks have been studied for many years in the hope of achieving a human-like performance in the field of speech, image recognition and pattern classification. These neural networks are composed of many nonlinear computational elements operating in parallel. Neural networks, because of their massive nature, can perform computations at a much 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 input signals.



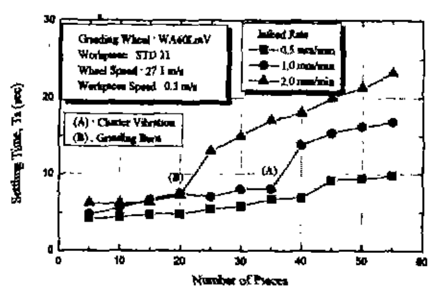
(a) Static power



(b) Dynamic power



(c) Power variation



(d) Settling time

Fig. 6 Characteristics of the power parameters

Learning in a neural network means finding an appropriate set of weights that are connection strengths from the elements to the other layer elements. In this study, the back propagation algorithm of neural networks, which is one of 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.[7]

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

$$\begin{aligned} \frac{\partial E_p}{\partial W_{ji}} &= \frac{1}{2}\sum_k \frac{\partial}{\partial W}\left(T_{pk} - O_{pk}\right)^2 \\ &= -\sum_k \left(T_{pk} - O_{pk}\right) f_k'\left(net_{pk}\right) W_{kj} f_j'(net_{pj}) X_{pj} \end{aligned} \tag{2}$$

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

where W_{ji} is the weight on the connection from the i th input element, α is called the learning-rate parameter, and i_{pj} and δ_{pk} are presented as follows:

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

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

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

4.2 Verification of Developed Detection System

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

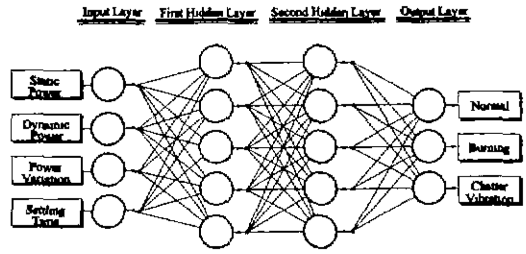


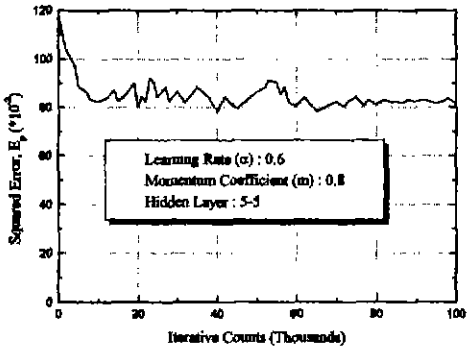
Fig. 7 Architecture of the used neural network

Trouble detection of the grinding process was conducted on a personal computer. Figure 7 presents the architecture of the neural network used in this study. Input units used the settling time, the static power, the dynamic power, and the power variation of acquired signals. Normal, burning, and chatter vibration states were occupied for output parameters, which had the interval values from 0 to 1. In comparison with these values of output parameters, the parameter of most major value means the state of grinding operation. Table 2 presents the values of input parameters and the teaching data (desired output) based on experimental results.

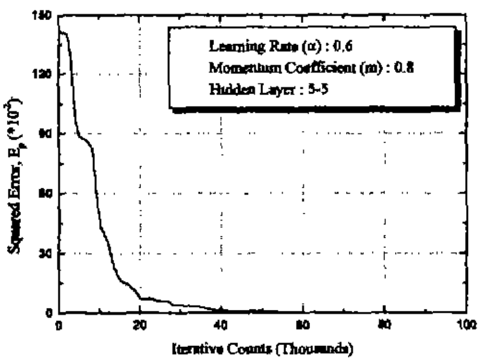
At the desired output, each pattern has the value of unity (only one parameter) or zero. For example, the neural net-

Table 2 Learning data used in the neural network

	Input Parameter				Desired Output		
	Ts	Ps	P_{fu}	Pv	Normal	Burning	Chatter
P-1	5.3	346.2	46.7	-22.3	1	0	0
P-2	5.8	352.7	48.5	18.6	1	0	0
P-3	5.4	370.4	44.3	2.3	1	0	0
P-4	6.4	374.2	48.6	-23.2	1	0	0
P-5	8 2	358.4	63.4	-22.7	0	1	0
P-6	10 4	364.3	76.2	-13.6	0	1	0
P-7	11.8	362.1	82.4	15.4	0	1	0
P-8	6.7	386.8	73.9	-44.1	0	1	0
P-9	7.5	472.8	72.3	18 4	0	0	1
P-10	8 7	384.2	76.5	62.7	0	0	1
P-11	11.5	432.3	75.3	93.2	0	0	1
P-12	11.2	428.4	84.7	14.5	0	0	1
P-13	17.7	413.2	78.6	12.8	0	0	1
P-14	18.9	463 9	144.3	118.1	0	0	1



(a) Squared error without clustering



(b) Squared error with clustering

Fig. 8 Squared error during the learning process

work is learned that the pattern P-1 listed in Table 2 is normal, P-5 is burning and P-9 is chatter vibration state being.

Fig. 8 Squared error during the learning process.

Figure 8(a) shows the behavior of the squared error during the learning process without clustering the power signal. As shown in Figure 8(a), a squared error cannot converge on a smaller value. In order to reduce the squared error, it is essential to cluster the range of input parameters. With the range analysis of acquired signals, clustering the range of power parameters listed in Table 3 was accomplished.

Table 4 shows new learning data based on the clustering. Figure 8(b) shows squared error during the learning process with clustering the power parameters. As shown in Figure,

Table 3 Clustering the range of the power parameters

Parameters	Low : 1	Middle : 2	High : 3
Ps	Below 370 (W)	370~420 (W)	Over 420 (W)
Pflu	Below 50 (W)	50~80 (W)	Over 80 (W)
Pv	Below -20 (W)	-20~20 (W)	Over 20 (W)
Ts	Below 6 (sec)	6~12 (sec)	Over 12 (sec)

Table 4 Learning data based on the clustering

	Input Parameter				Desired Output		
	Ts	Ps	P_{flu}	Pv	Normal	Burning	Chatter
P-1	1	1	1	1	1	0	0
P-2	1	1	1	2	1	0	0
P-3	1	2	1	2	1	0	0
P-4	2	2	1	1	1	0	0
P-5	2	1	2	1	0	1	0
P-6	2	1	2	2	0	1	0
P-7	2	1	3	1	0	1	0
P-8	2	2	2	1	0	1	0
P-9	2	2	2	2	0	0	1
P-10	2	2	2	3	0	0	1
P-11	2	3	2	3	0	0	1
P-12	2	3	3	2	0	0	1
P-13	3	2	2	2	0	0	1
P-14	3	3	3	3	0	0	1

squared error converges on a small value and therefore learning process was carried out well. Recalled results that were obtained through the iterative learning from the established neural network are listed in Table 5. The output of the neural network coincides with desired output shown in Table 4. It means that this system for grinding trouble recognition is able to classify the grinding state.

Table 6 lists implementation results for new power data that were not learned in the previous step. In this case, output values of the neural network have a few changes compared with Table 4 and 5. Normal parameters shown in Table 6 have a higher concentration of unity value when normal the state of grinding operation is maintained, while others such as burning and chatter vibration parameters have a lower concentration when burning and chatter vibration state is generated. A few erroneous recognitions were

Table 5 Recalled results of the detection system

	Input Parameter				Desired Output		
	Ts	Ps	P_{flu}	Pv	Normal	Burning	Chatter
P-1	1	1	1	1	0.9572	0.0011	0.0017
P-2	1	1	1	2	0.9834	0.0002	0.0000
P-3	1	2	1	2	0.9712	0.0000	0.0987
P-4	2	2	1	1	0.9823	0.0001	0.00212
P-5	2	1	2	1	0.0391	0.9551	0.0005
P-6	2	1	2	2	0.0000	0.9549	0.1723
P-7	2	1	3	1	0.0000	0.9186	0.0729
P-8	2	2	2	1	0.0002	0.9994	0.0196
P-9	2	2	2	2	0.0000	0.1161	0.8692
P-10	2	2	2	3	0.0281	0.0000	0.9929
P-11	2	3	2	3	0.0189	0.0000	0.9999
P-12	2	3	3	2	0.0003	0.0031	0.9854
P-13	3	2	3	2	0.0000	0.0002	0.9975
P-14	3	3	3	3	0.0000	0.0009	1.0000

Table 6 Implementation results of the new data

	Input Parameter				Desired Output			Results
	Ts	Ps	P_{flu}	Pv	Normal	Burning	Chatter	
P-15	1	2	1	1	0.9774	0.1754	0.0000	Normal ○
P-16	2	2	3	1	0.9653	0.1683	0.2652	Normal ○
P-17	3	1	2	1	0.9964	0.0000	0.0388	Normal ○
P-18	1	2	2	1	0.0007	0.8608	0.1496	Burning ○
P-19	1	3	2	2	0.0023	0.7764	0.2423	Burning ○
P-20	1	3	3	1	0.0000	0.8757	0.1737	Burning ○
P-21	1	3	2	1	0.0000	0.4906	0.6594	Chatter X
P-22	2	3	2	2	0.0003	0.0025	0.7932	Chatter ○
P-23	2	3	3	3	0.0000	0.0283	0.7999	Chatter ○
P-24	2	2	3	3	0.0000	0.1570	0.8487	Chatter ○
P-25	3	1	2	3	0.1748	0.0005	0.8712	Chatter ○
P-26	3	1	3	3	0.0014	0.0605	0.8386	Chatter ○
P-27	3	2	2	3	0.0000	0.0000	0.8364	Chatter ○

made at the boundary point between burning and chatter vibration. Nevertheless lower concentrations and the erroneous results were encountered, the recognizable performance of the established system is very good. Figure 9 presents percentages of success rates according to the various layer structures in the established detection system.

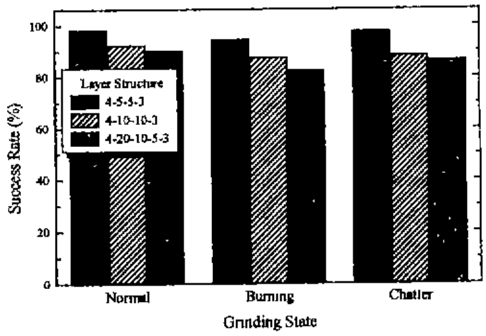


Fig. 9 Performances of the trouble detection system

From Figure 9, it is evident that the maximum performance is 95% above when the neural network is optimized. At all times, performances of trouble recognition are about 90%.

5. Conclusions

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

(1) Because of the grinding trouble, integrity deterioration of a damaged surface was distinctly verified. With increasing the number of grinding pieces, the values of surface roughness were slightly increased in the normal state of grinding, but rapidly increased in trouble states. It was seen in order to produce a satisfied product that grinding trouble such as burn and chatter vibration must be avoided with credible methods.

(2) To forecast the grinding states, the parameters of power signals were determined. Static power increased gradually in the machining process of the stable state. On the other hand, static power ascended excessively or decreased when the chatter vibration and the workpiece burning were generated respectively. Power variation of the stable state was nearly a constant but diverged from a rise and a drop with

chatter vibration and workpiece burning respectively. As trouble happened, the other parameters increased also.

(3) From the implementation results of computer simulation for new power data that were not learned, the normal parameter has a higher concentration of unity, while others such as burning and chatter vibration parameters are lower. A few erroneous recognitions were made at the boundary point between burning and chatter vibration. The maximum performance was 95% above when the neural network was optimized.

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