Intelligent Diagnosis of Grinding State Using AE and Power Signals
음향방출과 동력 신호에 의한 인공지능형 연삭상태 진단

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Key Words : Grinding Process(연삭공정), Power Signals(동력신호), Acoustic Emission Signals(음향방출신호), Neural Network(신경회로망)

요약 : 연삭가공은 나노스케일(Nano scale)의 미소한 입자 절삭날을 이용한 가공으로, 공작물의 표면을 경면(Mirror surface)으로 가공할 수 있어 제품의 최종 마무리공정으로 사용되어 왔다. 그러나 연삭공정에 있어서는 공구(연삭숫돌)의 수명이 다하거나 가공계(Machining system)가 불안정해지면 채터진동과 연삭버닝 등의 현상이 발생하여 가공물의 표면품위를 저하시키는 요인으로 작용하고 있다. 따라서 본 연구는 원통플런지 연삭공정을 대상으로 공작물에서 발생하는 음향방출 신호와 연삭기 주축 모터의 동력 신호를 연삭가공 중에 검출하고, 이를 신경회로망에 적용하여 연삭가공 상태를 진단하는 시스템을 구축하고, 그 성능을 평가하였다.

1. Introduction

At the present day, one of important grinding related researches is a realization of an on line diagnosis. The grinding process has machined fine products that cannot be met for constraints, such as surface roughness and geometric error, with traditional cutting processes. However, there are unique characteristics of the grinding process in tools, cutting conditions and a machining mechanism. The grinding process includes, therefore, many factors related to malfunction and the qualitative interactions between these factors cannot be understood yet[1,2]. A burn of a workpiece 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]. Another trouble is a chatter vibration that is a relative motion between the grinding wheel and the workpiece during the operation[4]. It is important to detect these fault phenomena during the machining process.

The grinding power is often used as a parameter for monitoring the grinding process. The power may also be used to monitor the effects of dressing. Empirical models are required to guide the selection of grinding conditions. Chen[5] reported that the effects of grinding conditions on grinding force and power were related to the shape of the idealized chip thickness. It was found that the grinding force and power could be related to the dressing time by considering the effective density of cutting edges on the wheel surface. The semi empirical model developed in this paper could be used to predict the variation of the grinding power during the wheel redressing life cycle.

I. Inasaki[6] introduced a monitoring and controlling system for the cylindrical grinding process with experimental verification. The acoustic emission (AE) sensor was used in his system. According to his assertion, most of the problems in the grinding process could be detected and furthermore, the grinding cycle could be automatically optimized.

This paper proposes the diagnostic scheme of a grinding state in the neural network using the power signal and the AE signal. The scheme

접수일 : 2002년 1월 5일
곽재섭, 하만경 : 부경대학교 기계공학부

utilizes the static and dynamic components of power signals and also the root mean square (RMS) and fast Fourier transform (FFT) components of AE signals as the inputs of the neural network. The relationship between the change of signal parameters and the trouble was also discussed.

2. Grinding fault

Grinding process is often used for the final finishing of a component because of their ability to satisfy strict requirements of the surface roughness. However, in case of the grinding fault generation, an allowable range of the surface roughness is not maintained.

Fig. 1 Percentage of influential factors to grinding burn[7)]

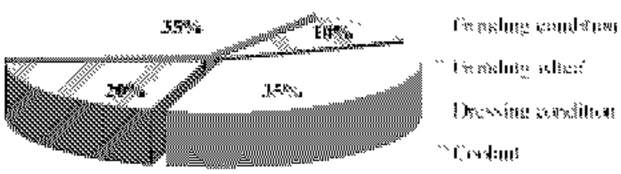


Fig. 2 Percentage of influential factors to chatter vibration[7)]

Grinding fault phenomena are affected by many influential factors that are mainly classified into the grinding condition, the grinding wheel, the dressing condition and the coolant. Fig. 1 describes a percentage of influential factors about the grinding burn. It is seen that the machining condition more affects the grinding burn than others. Fig. 2 shows a percentage of influential factors about the chatter vibration. The machining condition and the dressing condition dominantly affect the chatter vibration. This is known that if an adequate dressing was not conducted before the grinding, the grinding fault phenomena are easily generated. Moreover, a correct selection of the machining condition is more important about avoiding fault phenomena.

A burn of a workpiece is a kind of the irreversible change at a micro structure of the surface layer and it is taken place under the action of a continuous high temperature at grinding zone. An visual observation of the burn is due to temper colors of very thin oxide layers on the workpiece surface. These layers for ferrous materials are mainly composed of Fe_2O_3, Fe_3O_4, and FeO layers from free surface. At the onset of grinding burn, a grinding force and a wheel wear rate increase sharply, and a surface roughness deteriorates. The burn of the workpiece often occurs, especially with adhesive materials. Metals adhering between voids within a grinding wheel block up a machining action.

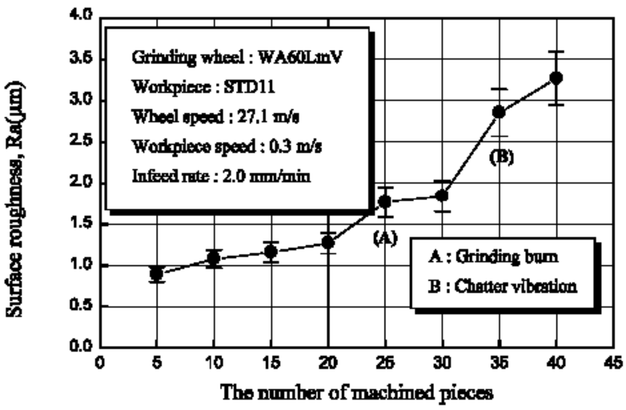


Fig. 3 Relationship between a surface roughness and the number of machined pieces

Therefore, the grinding process will be an abnormal state and the grinding temperature is rapidly arisen about 1,000℃. As this effect of the arisen temperature, the workpiece surface is burnt.

When a chatter vibration is generated on the ground surface, the grinding process is under unstable state. Chatter marks normal to the grinding direction may be easily seen on the ground surface and a deterioration of the surface roughness is evident. Fig. 3 shows a relation ship between a surface roughness and the number of machined pieces. The values of the surface roughness are slightly increased in normal state of grinding, but rapidly increased when fault phenomena generate. It can be seen in order to produce a satisfactory product that fault phenomena, such as the burn and the chatter vibration, must be detected in early stage and avoided as much as possible.

3. Preliminary experimentation and results

3.1 Experimentation

An experimental setup is shown in Fig. 4. A series of grinding tests were conducted on a cylindrical grinder with a 228mm diameter WA60LmV wheel that is mostly occupied with a general purpose in workshop. STD11 specimen was tested. A power monitor and an AE sensor were applied to the diagnosis technique.

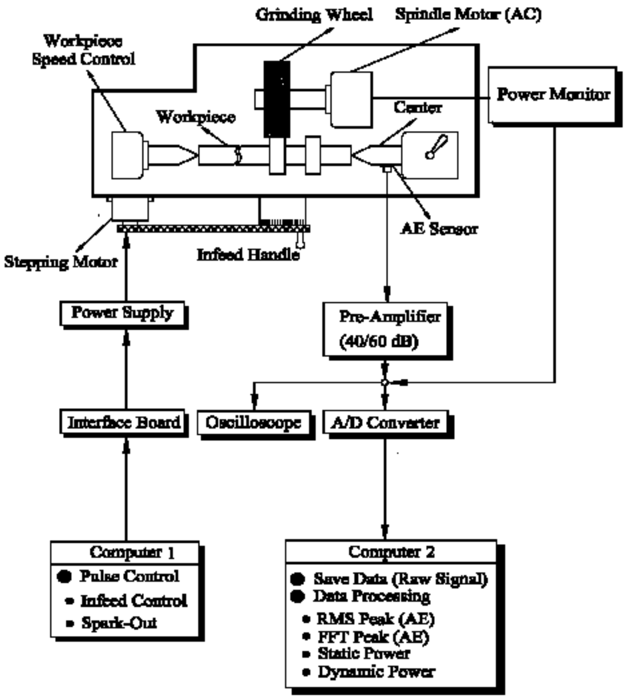


Fig. 4 Experimental setup for acquiring signals from an AE sensor and a power monitor

A power monitor with 10kHz sampling frequency was used to measure power signals during the grinding process. Signals outrunning the power monitor were converted analog to digital. Digitalized signals stored in a personal computer.

An AE sensor with a frequency response of wide bands was attached to the dead center of a grinding machine. To avoid signal attenuation during the transportation from the sensor to a computer, a pre amplifier was connected. The raw AE signals were digitized using an A/D converter and stored using a personal computer for later analysis. An oscilloscope visualized power and AE signals.

Table 1 Experimental specifications and conditions

Items	Specifications and conditions
Grinding wheel	Type : WA60LmV Size : ϕ228 × 24 mm
Workpiece	Material : STD11 Hardness : H_RC 45~47
Wheel speed	V_s = 27.1 m/s (1,800 rpm)
Workpiece speed	V_w = 0.20 ~ 0.40 m/s
Infeed rate	0.5, 1.0, 2.0 mm/min
Cutting fluid	Dry cut
Dressing conditions	Depth of cut : 0.015 mm Lead : 0.020 mm/rev

For a constant infeed rate, a stepping motor was attached in machine and a computer controlled the motor. Experimental conditions used in measuring power signals were listed in Table 1.

3.2 Parameter selection and variation behavior

3.2.1 In the case of grinding power signal

Fig. 5 shows a typical trend of a power signal changed during the grinding process. In general, a grinding power increases rapidly with the contact between the wheel and the workpiece. It appears an initiative point of a grinding cycle. After several times, the grinding power settles down a certain level of the amplitude that is a static power. With the continuous grinding, the grinding power maintains mostly its same level. When separation between the wheel and the workpiece is progressed, the grinding power has seriously a reduction of its level. This variation of the grinding power composes the grinding cycle. Normally, the static power remains with a constant magnitude, but in many times, when a fault generates, its level happens to change. At the chatter vibration and the burn, static powers have a magnitude significantly different than the aspects of the stable state. Therefore, grinding states can be detected with monitoring static powers. To forecast the grinding state, parameters of power signals must be determined more.

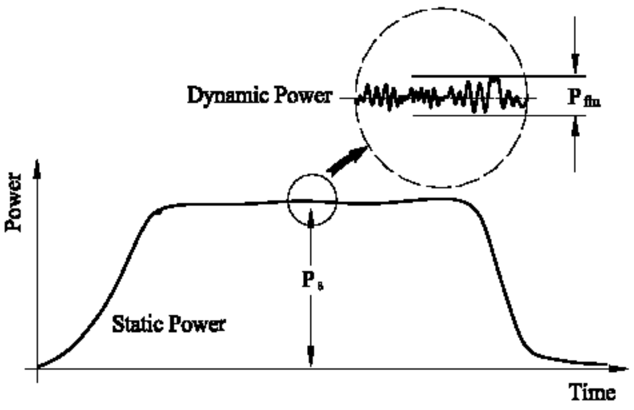
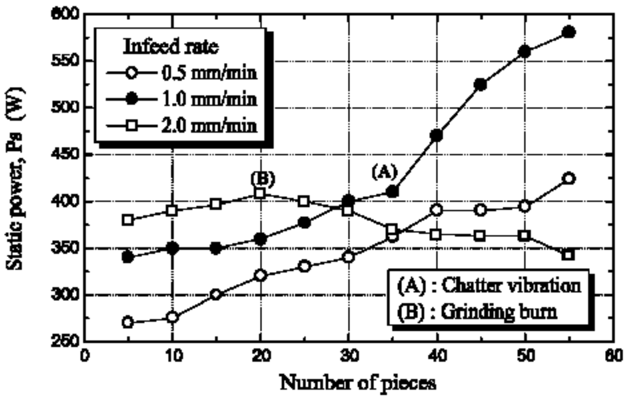


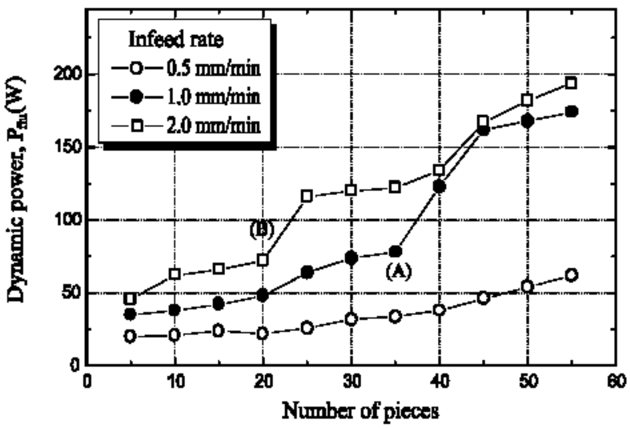
Fig. 5 Definition of the power parameters for diagnosis of grinding fault

As shown in Fig. 5, these parameters are Ps and Pflu. The static power P_s is the power magnitude from the starting point to the settling point according to the vertical axis and presents an absolute level of the power generated in the grinding zone. The 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.

As shown in Fig. 6, these parameters increase or decrease dramatically in generation of not only the chatter vibration but also the burn of a workpiece. If these parameters are used for detecting fault phenomena of a grinding process, it will be more effective.



(a) Static power



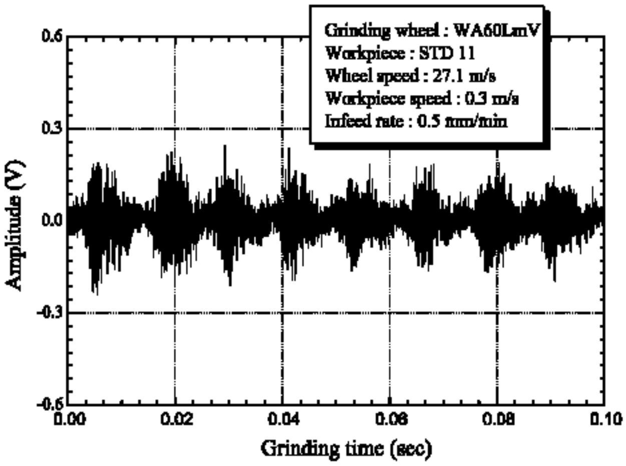
(b) Dynamic power

Fig. 6 Variation behavior of power parameters

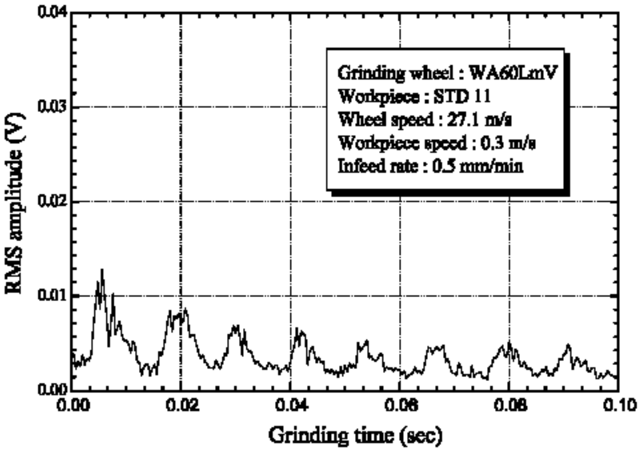
3.2.2 In the case of AE signal

Fig. 7 (a) shows typical AE signals obtained from the grinding operation. As other metal cutting processes, the raw signal forms are continuous types and sharply fluctuate with grinding time. The amplitude of raw signals increases according to the number of ground workpiece, but because of the similitude in signals it is not always distinguished either the grinding state is stable or unstable from the raw signal form. Therefore, other analytic parameters are needed to identify the grinding state.

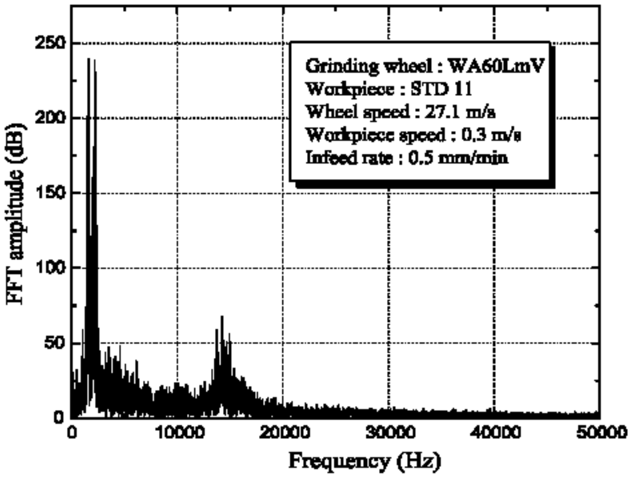
Fig. 7 (b) presents the RMS signal of the raw signal shown in Fig. 7 (a). The changes in AE signals are easily verified by an AE RMS level and a distinctive type. The result of the frequency analysis of the raw signal is drawn in Fig. 7 (c). The FFT amplitude is evident,



(a) Raw signal form



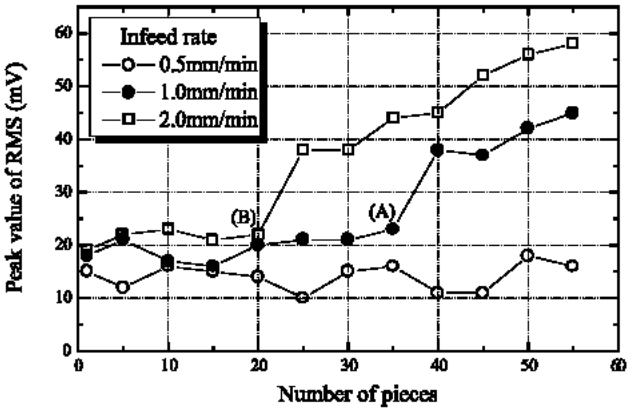
(b) RMS signal form



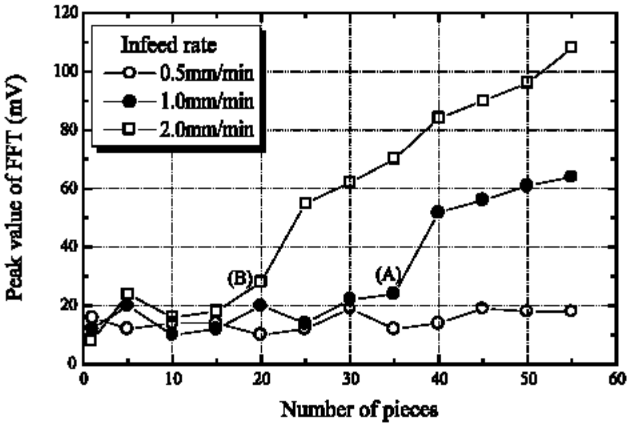
(c) FFT signal form

Fig. 7 AE raw and post processed signal forms

especially when the frequency ranges reach about 1.8kHz and 15kHz. Because the wheel rotational frequency is about 30Hz, it can be seen that a trouble frequency is an integer multiple of the wheel rotational frequency.



(a) RMS peak



(b) FFT peak

Fig. 8 Variation behavior of AE parameters

Fig. 8 (a) shows the peak values of AE RMS. It was found that the more the in feed rates are applied, the higher the level of the RMS peak became. At the time of a trouble generation, the RMS peak was increased rapidly.

Fig. 8 (b) presents the peak values of AE FFT. The FFT level was maintained to a particular piece, as an example, the 20th piece with 2.0mm/min in feed rate, and after the 20th piece, the peak level increased suddenly.

4. Intelligent diagnosis of grinding state

4.1 Neural network

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.

In this study, the back propagation algorithm of neural networks that is one of the various learning modes is used. This algorithm in the multi layer perceptron has made networks the most popular among researchers and users of neural networks. For the purpose of a pattern classification, the squared error cost function, which has most frequently used in the neural network and which has proven to converge into a small error is defined as[8)]

$$E=\frac{1}{2}\sum_{i=1}^{p}\| y^{(i)}-d^{(i)}\|^{2} \qquad (1)$$

Where the superscript i is an ith input pattern. The y and the d are a calculated output and a desired output of this pattern. The back propagation algorithm is a gradient descent method to minimize the squared error cost function. The procedure of a learning in back propagation algorithm can be summary as follows.

Step 1. Initialize the weights to small random values.

Step 2. Randomly choose an input pattern.

Step 3. Propagate the signal forward through the network.

Step 4. Compute δ_i^L in the output layer $(o_i = y_i^L)$

$$\delta_i^L = g'(h_i^L)\,[d_i^U - y_i^L] \qquad (2)$$

Where h_i^L represents the net input to the ith unit in the Lth layer, and g' is the derivative of the activation function g.

Step 5. Compute the deltas for the preceding layers by propagating the errors backwards;

$$\delta_i^l = g'(h_i^l)\sum_j w_{ij}^{l+1}\,\delta_j^{l+1} \qquad (3)$$

for $l=(L-1),\ldots.,1$.

Step 6. Update weights using

$$\Delta w_{ji}^l = \eta\,\delta_i^l\,y_j^{l-1} \qquad (4)$$

Where η is a coefficient of the lear ningrate parameter.

Step 7. Go to step 2 and repeat for the next pattern until the error in the output layer is below a pre specified threshold of a maximum number of iterations is reached.

4.2 Fault diagnostic results

The performance of neural networks is widely different from others in accordance with the selection of a learning rate and a structure of hidden layers. Therefore, it is necessary to select the adequate learning rate and the structure

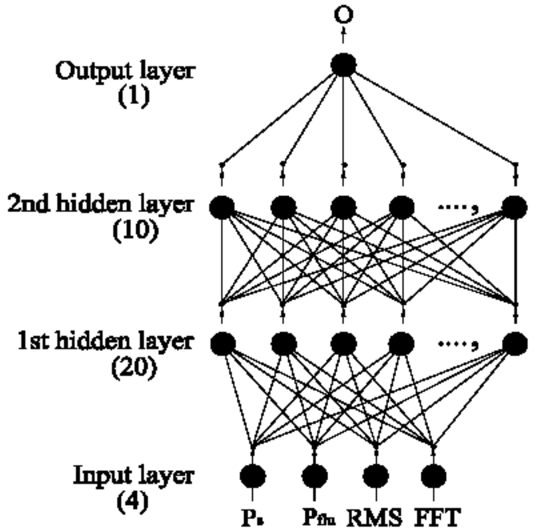


Fig. 9 Structure of the diagnostic neural network

Table 2 Learning patterns for grinding state diagnosis

Input units				Output unit
P_s (w)	P_{flu} (w)	RMS (mV)	FFT (mV)	O
273	28	12	11	0
295	34	14	24	0
365	64	14	27	0
373	79	19	13	0
387	43	21	16	1
398	48	23	32	1
403	57	32	17	1
409	83	24	19	1
417	88	27	42	2
423	106	28	47	2
436	95	29	48	2
448	116	37	50	2

of hidden layers. Through preliminary study, the coefficient of the learning rate was determined as 0.6. The structure of hidden layers was composed of two layers.

As shown in Fig. 9, the architecture of the neural network was used. Input units were used the P_s, P_{flu}, RMS peak and FFT peak. An output unit was occupied. The output unit had interval values from 0 to 2. As the result of the output unit, grinding states were made a diagnosis of normal and fault states.

Table 2 lists learning patterns for the grinding state diagnosis with the sensor fusion. If the listed input patterns appear during the learning process, the neural network understands the grinding state from output values as normal (value 0), burning (value 1), and chatter vibration (value 2). For the effective learning, the number of learning patterns was selected as 12 patterns. If more learning patterns were used, the learn error could not converge. The learning process was carried out successfully.

Table 3 Diagnostic results of new patterns

Input units				Output unit	Diagnosis	
P_s (w)	P_{flu} (w)	RMS (mV)	FFT (mV)	O		
271	66	23	11	0.02	Normal	(Correct)
296	83	32	14	0.02	Normal	(Correct)
429	34	22	18	0.14	Normal	(Correct)
324	76	26	13	0.98	Burning	(Correct)
362	107	29	26	1.04	Burning	(Correct)
243	116	35	17	1.21	Burning	(Correct)
289	121	19	13	1.64	Chatter	(Incorrect)
420	72	34	35	1.97	Chatter	(Correct)
395	94	37	39	1.93	Chatter	(Correct)
431	54	32	43	1.98	Chatter	(Correct)
457	65	25	52	1.96	Chatter	(Correct)

Table 3 presents diagnostic results of new patterns that are not learned at the previous step. Because of pattern indefiniteness between the grinding burn and the chatter vibration, some erroneous diagnosis were made. To reduce the erroneous diagnosis effectively, it is necessary to define adequate learning patterns. Nevertheless this diagnostic method using sensor fusion is available for grinding process.

Fig. 10 presents the successful diagnostic percentage in accordance with the variation of layer structures. A few erroneously diagnostic results were made in the boundary between the grinding burn and the chatter vibration. As shown in Fig. 10, it is seen that the maximum percentage of the successful diagnosis is about 95%.

In view of the diagnostic results, the sensor fusion technique of the power signal and AE signal is able to detect the fault phenomena in grinding process.

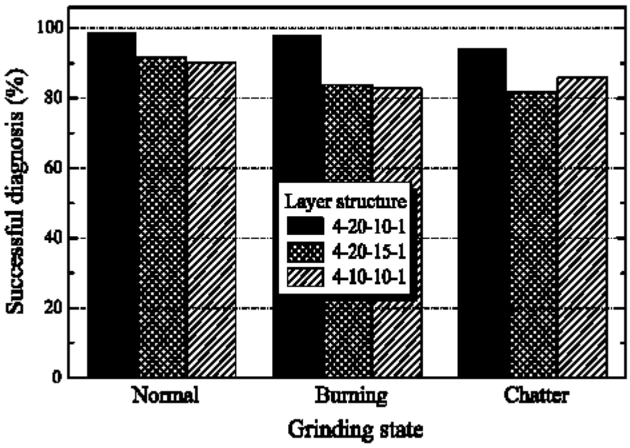


Fig. 10 Successful diagnostic percentage in accordance with the variation of layer structures

5. Conclusions

In this study a diagnostic technique for the fault phenomena, such as the chatter vibration and the grinding burn, has been developed in the grinding process.

When fault phenomena occurred, the values of the all AE parameters increased rapidly. The more the in feed rates were applied, the higher the levels of AE parameters became. The FFT amplitude was evident when the frequency ranges reached about 1.8kHz and 15kHz. Power parameters increased or decreased with the onset of the fault phenomena.

The AE and the power parameters were used as input units of the neural network. From a performance evaluation of the learned neural network, the maximum percentage of the successful diagnosis was obtained about 95%.

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