Detection Technique of Fault Phenomena Using Power Parameters in Grinding Process

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ABSTRACT

The grinding process has been mainly used for finishing metal products as final machining stage. But chatter vibration and burn of a workpiece have a bad effect on the machined surface and should be detected in modern grinding process. This paper deals with a fault detection of the cylindrical plunge grinding process by power parameters. During the grinding process the power signals of an induced motor were sampled and used to determine the relationship between fault and change of power parameters. A neural network was used for detecting the grinding fault and an influence of power parameters to the grinding fault was analyzed.

Keywords: Grinding process, Power parameters, Fault detection, Neural network

1. Introduction

At the present time, one of important grinding related researches is a realization of an on-line fault detection system. 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 was related to the shape of the idealized chip thickness. It was found that the grinding force and power could be related to the dressing operation 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.

This paper proposes a neural-network-based fault detection scheme. The scheme utilizes the static and dynamic components of power parameters as the input to the neural network. The relationship between the change of parameters and the fault was also discussed.

2. Bad Effect of Fault Phenomena

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.

Grinding fault phenomena are affected by many influential factors that are mainly classified into the grinding condition, the grinding wheel, the dressing

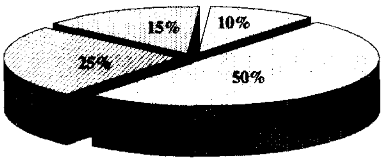


Fig. 1 Percentage of influential factors to grinding burn[6].

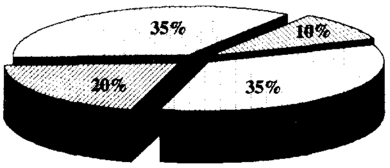


Fig. 2 Percentage of influential factors to chatter vibration[6].

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 Fe2O3, Fe3O4, 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. Therefore,

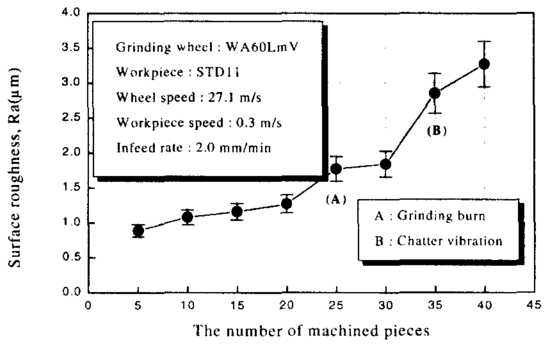


Fig. 3 Relationship between a surface roughness and the number of machined pieces.

the grinding process will be an abnormal state and the grinding temperature is instantaneously 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 relationship 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. Experimentation and parameter selection

3.1 Experimentation

An experimental setup is shown in Fig. 4. 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. Specimen STD11 that is preferred to the die and the mold material was tested. A power monitor with 10 kHz sampling frequency was used to measure power signals during the grinding process. An oscilloscope visualized power

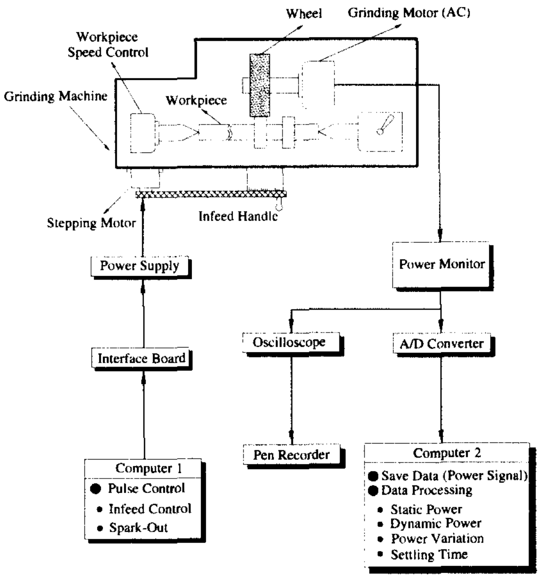


Fig. 4 Experimental setup for acquiring power signals from an induced grinding motor.

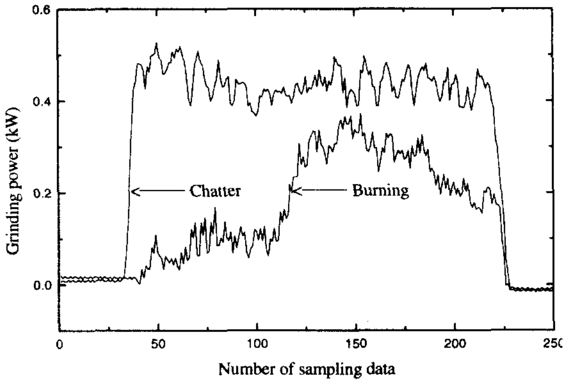


Fig. 5 An example of the grinding power signals in cases of chatter and grinding burning.

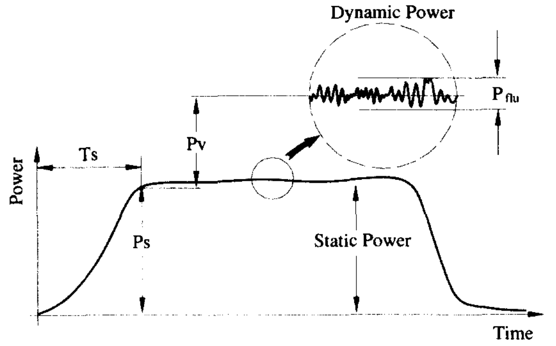


Fig. 6 Definition of the power parameters for detecting fault phenomena.

signals obtained and pen recorder plotted signals. Signals outrunning the power monitor were converted analog to digital. Digitalized signals stored in a personal computer.

The stored signals were analyzed and they were utilized for defining the power parameters that reveals a cue of fault phenomena. 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.

Table 1 Experimental specifications and conditions

Items	Specifications and conditions
Grinding wheel	Type : WA60LmV
	Size : ϕ228 × 24
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 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 Parameter selection

Fig. 5 presents an example of the grinding power signal generated in cases of chatter and grinding burning. It shows that grinding power signals of chatter and grinding burning differ each. Therefore it needs to define the power parameters that make the detection of a grinding state easy.

Fig. 6 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 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.

As shown in Fig. 6, these parameters are Ts, Ps, Pflu, and Pv. The Ts is a settling time that is calculated with a starting point of a slope of 30° and a final point of a slope of 5° from the horizontal line. To avoid the instantaneous change of slope due to an abnormal machining condition during grinding process, these slopes were defined as the change of the mean power of 20 sampled data per each time interval.

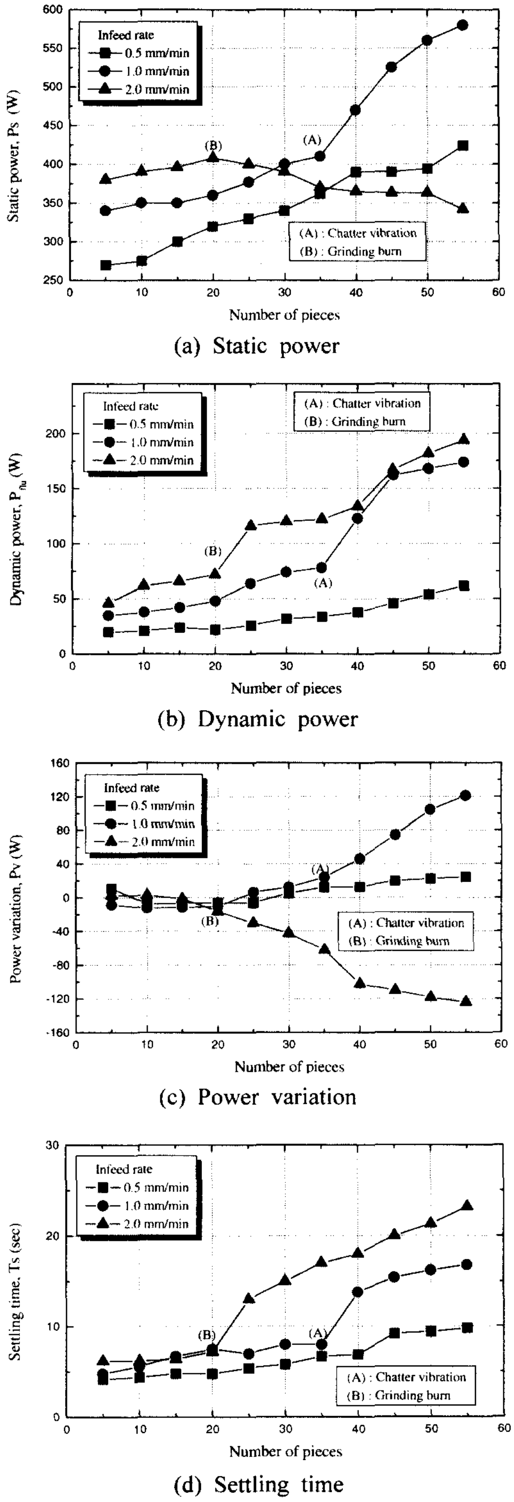
The static power Ps is the power magnitude from the starting point to the ending point of the settling time according to the vertical axis and presents an absolute level of the power generated in the grinding zone. The dynamic power Pflu is a power component of the high frequency and it fluctuates around 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, the 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.

As shown in Fig. 7, 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.

4. Fault detection technique

4.1 Neural network algorithm

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



(a) Static power

(b) Dynamic power

(c) Power variation

(d) Settling time

Fig. 7 Experimental results of power parameters 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.

The ability to learn is a fundamental trait of the neural network. Although a precise definition of learning is difficult to formulate, a 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. 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[7]

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

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 learning-rate 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 Neural network structure and results

According to the selection of a learning rate, the performance of neural networks is widely different from others. Therefore, it is necessary to optimize the neural network with the correct learning rate. Through preliminary study, the coefficient of the learning rate was determined as a value of 0.6. In general, during the learning process the squared error method with raw power signals frequently fails down convergence, so the squared error cannot converge on a smaller value. In order to reduce easily the squared error, it is essential to group input parameters with the several ranges. For the purpose of reducing the squared error, grouping the range of power parameters was achieved as listed in Table 2. It was made based on the preliminary experimental data analysis According to this grouping, the neural network understands any level value of power parameters as the specified grouping value from 1 to 3.

Fig. 8 presents the architecture of the neural network used. Input units were used the Ps, Pv, Pflu, and Ts parameters of the power signal. Output units were occupied as the normal(On), the burn(Ob), and the chatter vibration(Oc). Output units had interval values from 0 to 1. Through comparison with these output units after network calculation, a unit of the output layer with the major value means the state of the grinding process being. Table 3 lists learning patterns for detecting fault

Table 2 Grouping power parameters for learning

Group / Param.	1	2	3
P_s	below 400 (w)	400~420 (w)	over 420 (w)
P_{flu}	below 50 (w)	50~80 (w)	over 80 (w)
P_v	below -30 (w)	-30~30 (w)	over 30 (w)
T_s	below 4 (sec)	4~12 (sec)	over 12 (sec)

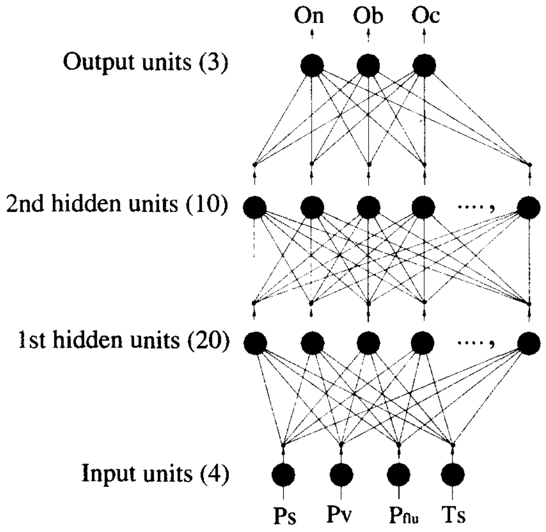


Fig. 8 Structure of the neural network.

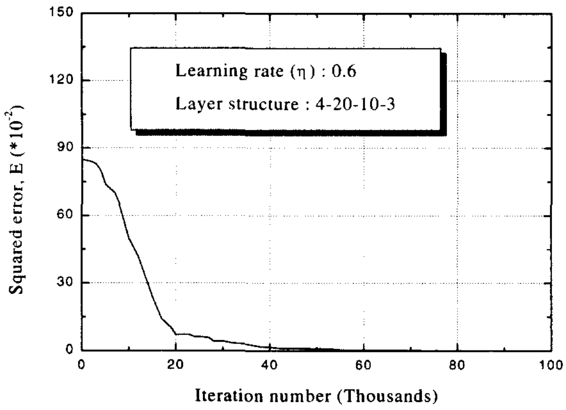


Fig. 9 Convergence of the squared error during the learning process.

Table 3 Learning patterns for detecting faults from change of power parameters

Input units				Output units		
T_s	P_s	P_{flu}	P_v	O_n	O_b	O_c
1	1	1	1	1	0	0
1	1	1	2	1	0	0
1	2	1	2	1	0	0
2	2	1	1	1	0	0
2	1	2	1	0	1	0
2	1	2	2	0	1	0
2	1	3	1	0	1	0
2	2	2	1	0	1	0
2	2	2	3	0	0	1
2	3	2	3	0	0	1
3	2	2	2	0	0	1
3	3	3	3	0	0	1

Table 4 Recalled results with a learned neural network

Input units				Output units		
T_s	P_s	P_{flu}	P_v	O_n	O_b	O_c
1	1	1	1	0.972	0.001	0.001
1	1	1	2	0.984	0.001	0.001
1	2	1	2	0.971	0.001	0.098
2	2	1	1	0.987	0.001	0.002
2	1	2	1	0.031	0.955	0.001
2	1	2	2	0.017	0.954	0.172
2	1	3	1	0.026	0.918	0.072
2	2	2	1	0.024	0.999	0.019
2	2	2	3	0.012	0.116	0.969
2	3	2	3	0.016	0.002	0.999
3	2	3	2	0.015	0.001	0.997
3	3	3	3	0.013	0.001	0.996

phenomena from the change of power parameters. For the successful learning and the fault detection with a learned neural network, the learning pattern were selected carefully. Patterns for normal, burning and chatter vibration were 4 each. If more learning patterns were used, the error could not converge during the iterative learning process.

Fig. 9 shows the squared error during the learning process with grouping power parameters. As shown in Fig. 9, the squared error converges on a small value and, therefore, the learning process was carried out well. It means that this strategy for detecting the fault phenomena is able to classify the grinding states.

Table 4 lists recalled results with a learned neural network. When the value of output units was compared with output value listed in Table 3, the fact that the learning is well done may be seen.

Table 5 presents implementation results of a new data set that is not learned at the previous step. The symbol O means that the detection of the neural network is true and the × is fault. Some erroneous detection were made.

Table 5 Implementation results of a new data set

Input units				Output units			Result
T_s	P_s	P_{flu}	P_v	O_n	O_b	O_c	
1	2	2	1	0.877	0.175	0.002	Normal ○
1	2	3	1	0.865	0.168	0.265	Normal ○
3	1	2	1	0.996	0.001	0.038	Normal ○
1	2	2	1	0.001	0.860	0.149	Burning ○
1	3	2	2	0.002	0.776	0.242	Burning ○
1	3	3	1	0.001	0.975	0.173	Burning ○
1	3	2	1	0.001	0.490	0.659	Chatter ×
2	2	2	2	0.002	0.002	0.993	Chatter ○
2	2	3	2	0.001	0.028	0.999	Chatter ○
2	2	3	3	0.001	0.157	0.998	Chatter ○
3	1	2	3	0.174	0.000	0.871	Chatter ○
3	1	3	3	0.001	0.060	0.938	Chatter ○
3	2	2	3	0.001	0.002	0.936	Chatter ○

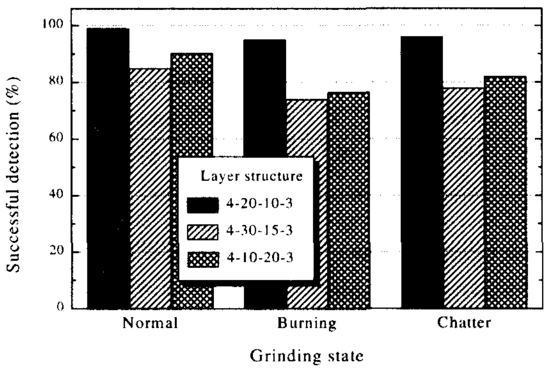


Fig. 10 Successful detection percentage according to various layer structures.

Fig. 10 presents the successful detection percentage according to various layer structures in the achieved fault detection system. A few erroneous detections were made in the boundary between the burn and the chatter vibration. Nevertheless some erroneous results were encountered, the performance of the fault detection was good. From the Fig. 10, it is seen that the maximum successful detection is about 95% when the layer structure of a neural network is optimized.

4.3 Analysis on the influence of parameters

To improve the performance of a successful detection, an analysis on the influence of power parameters to the fault phenomena must be conducted. Therefore, from the results of the experimentation and the detection system, a relationship between the range of each parameter and the fault phenomena was obtained.

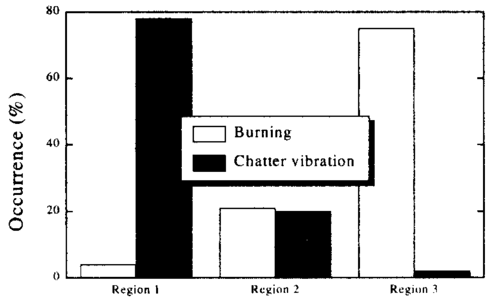
Fig. 11 presents a percentage of the fault occurrence according to a grouping region of power parameters. From the results as shown in Fig. 10, it may be seen that the grinding burn and the chatter vibration during the grinding process can be effectively monitored through detecting a change of the static power. In general, the grinding burn was frequently generated at region 3 of the static power but the chatter vibration was easily appeared at region 1 as shown in Fig. 11 (a). It was seen that the static grinding power either decreases due to the chatter vibration which produces an increased rate of a bond rupture or increases due to the grinding burn and wheel loading. At this time, the grinding wheel has to be redressed.

The dynamic power, in Fig. 11 (b), had the region 3 when the grinding burn and the chatter vibration were generated. It means that the grinding state with the fault phenomena is unstable much more and that the grinding power is seriously fluctuated. The settling time and the power variation were in the region 3 coinciding with the occurrence of the fault phenomena as shown Figs. 11 (c) and (d). In view of the analysis results so far achieved, the static power parameter is preferable to detect the fault phenomena in grinding process and more effect parameters should be sought to improve the successful detection.

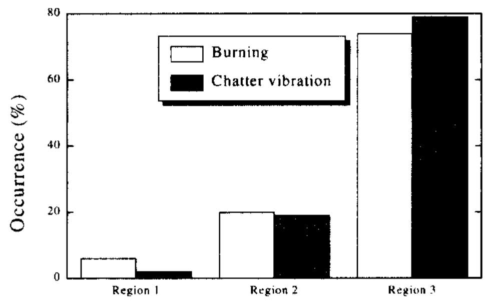
5. Conclusions

To detect the fault phenomena in grinding process, a new technique using power parameters was applied. Due to the fault phenomena, the trend of a surface integrity deterioration was sharply occurred.

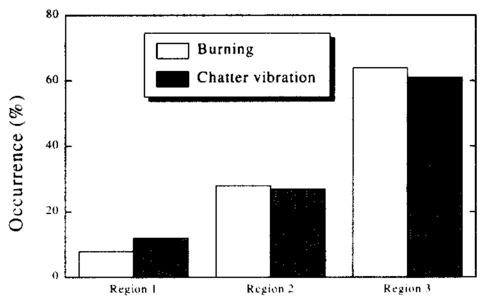
Power parameters such as the static power, the dynamic power, the power variation and settling time were determined for detecting fault phenomena. After grouping power parameters, then they were used as input units of the neural network. Through the learning process of a constructed neural network, the squared error was converged at a small value. As a performance of the learned neural network, the maximum successful detection was about 95% when the layer structure of the neural network was optimized.



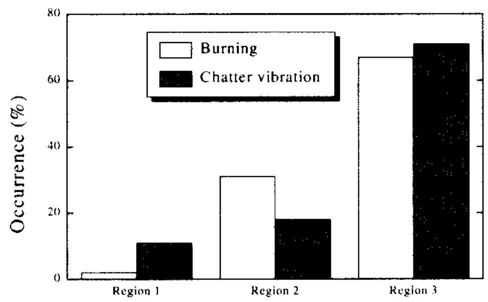
(a) Static power



(b) Dynamic power



(c) Settling time



(d) Power variation

Fig. 11 Percentage of the fault occurrence according to the grouping range of power parameters.

The analysis on the influence of power parameters wes conducted to obtain the relation between the power parameters and the fault phenomena. The static power was preferable to detect the fault phenomena in grinding process.

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