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Evaluation of Pre-estimation Model to the Inprocess Surface Roughness for Grinding Operations

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ABSTRACT

In grinding operations, one of the most important problems is to increase efficiency of process. In order to achieve this purpose, it is necessary to administer the tool life of grinding wheel and to optimize grinding conditions. Frequently dressing result in lowering the process efficiency remarkably and makes production cost high. On the other hand, grinding with a worn wheel causes the workpiece surface roughness to increase and often results in the occurrence of such troubles as chatter vibration and burning.

Key Words: Grinding Operation, Pre-estimation Model, Inprocess Measuring Method, Surface Roughness, Neuro and Fuzzy Model, Neural Network

I. Introduction

It can be accomplished to DNC (direct numerical control and distributed numerical control) system adopted computer in the field of NC machine tools so that can be corresponded with mass production with small lot size type.

Especially, grinding operations can be easily achieved by developing the grinding wheel grits both high efficiency cutting and brittle and hardened material cutting.

Grinding wheel has a function of self-generation. Grinding cutting is obviously more efficient than plowing or rubbing, grit fracture and grit pullout are nature phenomena used to keep the grit sharp. As the grits become dull, cutting forces increase and there is an increased tendency for the grits to fracture or break free from the bonding materials.

There is a possible for optimum grinding conditions in terms of wheel depth of cut, wheel velocity, and workpiece velocity. But these optimum conditions are extremely limited region, and even though it can also be worked, grinding results are differentiated since it is affected by several external parameters unexpected factors.

Moreover, it is difficult to obtain a high quality and high precision products as grinding wheel surface can be changed in accordance with grinding time. In these reason, it is derived to diminish the surface roughness of workpiece quality in accordance with wheel geometric surface. Nevertheless, in this method, it can be derived with decreasing a grinding efficiency because of before occurring tool life as well as increasing a grinding cost so that consume a grinding wheel.

Therefore, in this paper, a basic study is structured for selection of pre-estimation model about surface roughness during the grinding process.

That is, this study is compared with value of surface roughness on the workpiece between pre-estimation model and measurement data for constructing the automatic grinding manufacturing system.

2. Establishment of Pre-estimation Model

This study structured on the inprocess surface roughness model for pre-estimating and measuring adopted in neural network and regression model, and also it analyzed between experimental results and presented simulated results of pre-estimation model.

2.1 Adoption of Neural Networks Model

The measurement of workpiece surface roughness can be tried by neural network of back-propagation model composed of three layers. BP (back-propagation) model has a set of neural networks model constructed in input, hidden, and output layer. The neuron constructed each layer has a weight value so that they will act together with connection for all neurons. Input data given in input layer can be transferred hidden and output layer calculating the weight value.

The shell of output layer modify between output and hidden layer and between hidden and input layer so that can they minimize the error for comparing the supervising data of category Eigen value with the input data. The output value alternated modification from output layer can be accessed the supervise data. For a series action, it can be classified with category presented supervise data.

Therefore there is a BP model modifying weight value by means of transferring inverse direction for the error between output of network and supervise data. The shell calculation each layers as follows;

Shell value of hidden layer: $V_{hj}=f(\sum_j W_{Hji}V_{Ij}+T_{Hj})$ (1)
Shell value of output layer: $V_{Oj}=f(\sum_j W_{Oji}V_{Hj}+T_{Oj})$ (2)

Where, Voj: jth number of shell value of output layer
VHj: jth number of shell value of hidden layer
VIj: jth number of shell value of input layer
Toj: jth number of shell boundary value of output laye
THj: jth number of shell boundary value of hidden layer
Woji: ith number of shell weight contained with jth number of shell boundary value of output layer.
WHji: ith number of shell weight contained with jth number of shell boundary value of hidden layer.

The output value of the function f(x) represented sigmoidal is ranged of $0 \leq Vxi \leq 1$. The initial value of weight WXji and boundary TXj can be established by random function.

$$f(x)=1/2(1+\tanh(x/\mu_0)) \quad (3)$$

Where, μ_0 is the parameter so as to determine the slope of sigmoidal function. Delta error between shell value of output layer and supervise data as follows;

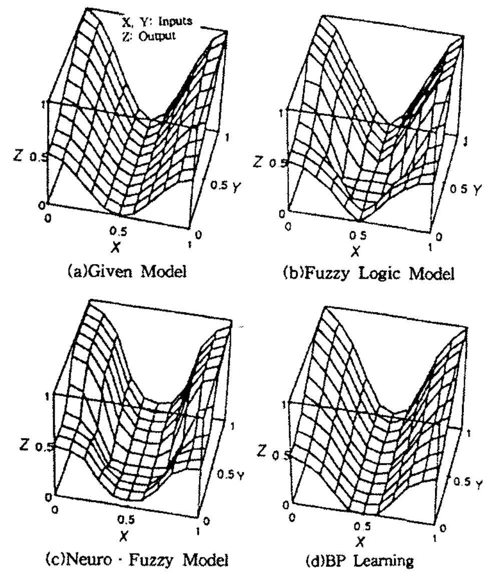

Fig. 1 Comparison of Pre-estimation for Applying the Surface Roughness

$$D_{oi}=2/\mu_0(S_i-V_{Oi})V_{Oi}(1-V_{Oi}) \quad (4)$$

Where, Doi: ith sell delta value of output layer, Voi: ith sell value of output layer, Si: ith sell supervise data

In equation (4), if it is applied to equation (5) given in delta of hidden layer using the calculated delta of output layer,

Hidden Layer Delta:
$$D_{Hi}=2/\mu_0(\sum_j D_{Oj}W_{Oji}-V_{Hi})V_{Hi}(1-V_{Hi}) \quad (5)$$

The hidden and output layer weight and the modification of boundary value are obtained as given in equation as follows;

Modification of output layer:
$$W_{Oji}=rW_{Oji}+aD_{Oj}V_{Hi} \quad (6)$$

Weight modification of output layer:
$$T_{Oj}=r'T_{Oj}+a'D_{Oj} \quad (7)$$

Modification of boundary value for hidden layer:
$$W_{Hji}=rW_{Hji}+aD_{Hj}V_{Ii} \quad (8)$$

Weight modification of hidden layer:
$T_{Hj}=r'T_{Hj}+a'D_{Hj}$ (9)

Where, a and a' are the modification coefficient and r and r' are the oblivion coefficient.

On the other hand, Fig.1 represents a comparison of between fuzzy inference model, neuro-fuzzy model, and pre-estimation value by BP learning. As shown in Fig.1, the best result is obtained from the neuro-fuzzy model.

2.2 Application of Linear Regression Model

The process of determining the constants a and b for the line (y=ax+b) that best fits a set of n data pairs (x1, y1) through (xn, yn) in a least-squares method is known as linear regression. The quantity to be minimized is

$$S=\sum_{j=1}^{n}[y_j-(ax_j+b)]^2 \quad (10)$$

The values of a and b that minimize S must satisfy the partial derivative conditions

$$\partial S/\partial a = \partial S/\partial b = 0 \quad (11)$$

The partial derivatives are given by

$$\partial S/\partial a = \sum\{-2x_j[y_j-(ax_j+b)]\} \quad (12a)$$
$$\partial S/\partial b = \sum\{-2x_j[y_j-(ax_j+b)]\} \quad (12b)$$

where the summation is understand from now on to be performed for f values from 1 to n. Substitution of the expressions for the partial derivatives into equation (11) gives us the two linear algebraic equations

$$a\sum([x_j]^2)+b\sum(x_j)=\sum(x_jy_j) \quad (13a)$$
$$a\sum(x_j)+nb=\sum(y_j) \quad (13b)$$

whose solutions are

$$a=\{n\sum(x_jy_j)-[\sum(x_j)][\sum(y_j)]\}/\{n\sum([x_j]^2)-\sum([x_j]^2)\} \quad (14a)$$
$$b=[\sum(y_j)-a\sum(x_j)]/n \quad (14b)$$

The coefficients in equation (14a,b) are derived on the assumption that the values of the independent variable x are correct and that all errors are in the values of the dependent variable y. This situation is obviously not true; if the roles of x and y are reversed, it would generally obtain a slightly different line from the least-squares approximation.

A crude measure of the how well the data is explained by a straight line is given by the linear correlation coefficient r, which may be computed from

$$r=\{n\sum(x_jy_j)-[\sum(x_j)][\sum(y_j]\}/\sqrt{t_xt_y} \quad (15a)$$
$$t_x=n\sum([x_j]^2-[\sum(x_j)]^2 \quad (15b)$$
$$t_y=n\sum([y_j]^2)-[\sum(y_j)]^2 \quad (15c)$$

Values of r may range from -1 to 1. If $|r|$ is exactly 1, the data is perfectly represented by the straight line. The values of X2 with (n−2) degrees of freedom is the value of S in Eq. (10) with the estimated coefficient values a and b. We may also relate X2 to the correlation coefficient through

$$X^2 = (1-r)^2(n-1)(s_y)^2 \quad (16)$$

in which (sy)2 is the sample variance of the y data.

The formulas for linear regression may be extended to models that can be recast in linear form. Let v be a variable that depends on another variable u, and let the model for v be described by

$$v = f(\alpha,\beta,u) \quad (17)$$

where, α and β are constant and coefficient, respectively. If it can recast equation(17) in the form

$$h(v)=C_1(\alpha,\beta)g(u)+C_2(\alpha,\beta) \quad (18)$$

It may equate x, y, a, and b in our earlier discussion to the quantities g(u), h(v), C1(α ,β), and C2(α ,β), respectively. The constants α and β are then obtained from the estimates of a and b by solving the equations [C1(α ,β)= a] and [C2(α ,β)= b].

3. Construction of Pre-estimation Model and Experimental Set-up

3.1 Experimental Set-up and Data Acquisition Method

Fig. 2 indicates the experimental set-up and data acquisition method for analyzing a given model. In this system, the information of workpiece surface roughness for plunge grinding operations is detected by grinding power signal, the merit of this method can be not only easily obtained for grinding characteristics, but also can be practically adopted in working area. But, limitation of application of grinding power signal and accelerometer signal, i.e. they can utilize the frequency of effect range.

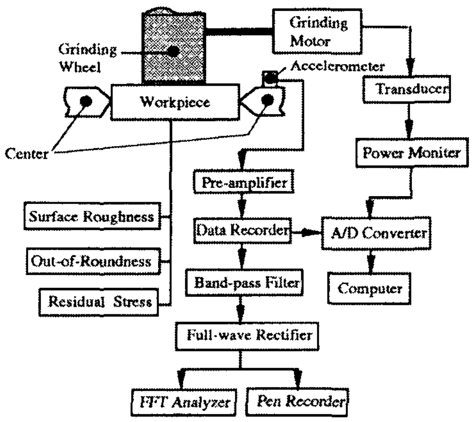

Fig. 2 Experimental Apparatus and Data Acquisition Method

Therefore, this system adopted a low-pass filter and high-pass filter. The range of former is limited with 10Hz range because the frequency of grinding wheel has a 40Hz so that grinding wheel revolution is 2400 rpm, and the latter is restricted with range of 1kHz so that it can be ignored a high-frequency signal. These signals are transformed into digital signal by A/D converter, and then accumulate in personal computer.

And also, to obtain an experimental data for pre-estimating of workpiece surface roughness, the experimental conditions, in this study, are subjected as grinding depth of cut is 5μ m/rev, 10μ m/rev, 20μ m/rev, and 30μ m/rev and each condition is carried out alternating 50~80 times, respectively. Among the experimental condition, this system can be adopted that the learning data for neural network is 10μ m/rev for the depth of cut, and the result from the obtained data are applied in the learning data for the purpose of grinding signal characteristics.

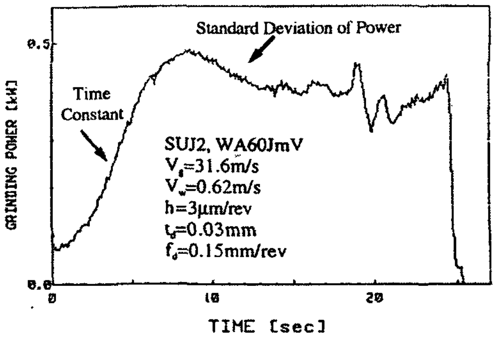

Fig. 3 Input Parameters for Pre-estimating of Grinding Surface Roughness

As shown in Fig.3, the input parameters for grinding power signal are adopted as standard of grinding power Pstd, peak value of power spectrum Pt, time instant Ts, and also the consist of neural network, as shown in Fig.4, is constructed in three layers such as three input layers, seven hidden layers, and one output layer.

The instant time Ts can be obtaind as y=a exp(-t/T) represented the regression experimental equation.

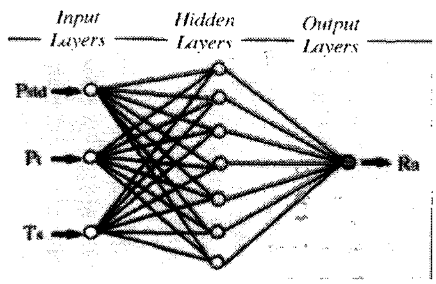

Fig. 4 Composition of Neural Networks Model in This System

3.2 Application Results of Neural Networks

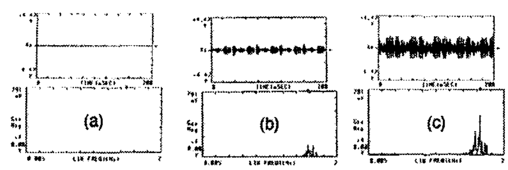

Fig. 5a Comparison of Power Spectrum and Power Signal According to Grinding Time

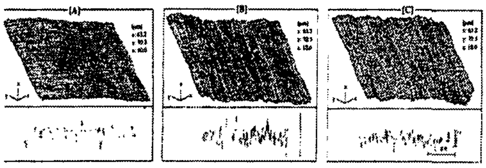

Fig. 5b Comparison of Surface Roughness According to Grinding Time

Fig. 5a and 5b indicate that comparision of between the power spectrum and grinding power signal and the surface roughness of workpiece obtaining a experimental measuring apparatus. As seen in this figure, grinding power signal and altitude of power spectrum is larger than grinding initial operation. And this result is affected upon the grinding signal and the surface roughness in accordance with grinding time.

Fig. 6 and Fig. 7 are comparison of neural network and neuro-fuzzy model on the conditions are given as depth of cut h=5, 10, 20μ m/rev, workpiece

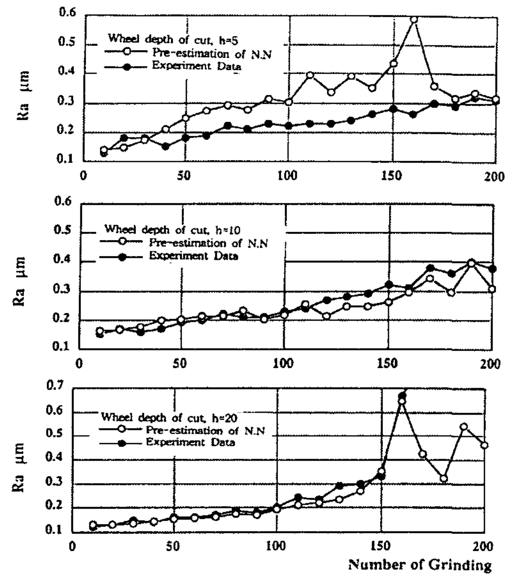

Fig. 6 Comparison of Neural Networks and Experimental Data

Vw=0.62m/s, Vg=31.6m/s, and workpiece is SUJ2, for the pre-estimation result and experimental results. As seen the results given in Fig. 6 and Fig. 7, though the result between pre-estimation and experimental data have a somewhat difference both sides, the rough grinding generally has a reliability on the pre-estimation model.

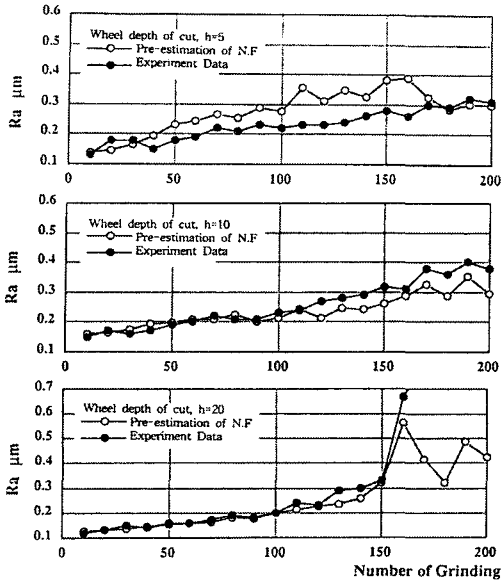

Fig. 7 Comparison of Neuro-Fuzzy and Experimental Data

And also, Fig. 8 indicates the change of average surface roughness Ra for the three parameters such as Pstd, Pt, Ts. As shown in Fig. 8, in the case of depth of cut h=10μ m/rev, the change of input parameter of neural network for the workpiece surface roughness is better adopted on the learning data since it is given in the medium value in comparison of the other grinding conditions. Therefore, this study used to neuro-fuzzy model for learning conditions.

Fig. 9 represents the inference method for driving inferring results in the case of neuro-fuzzy model. That is, the inference method, in this system, is applied as follows;

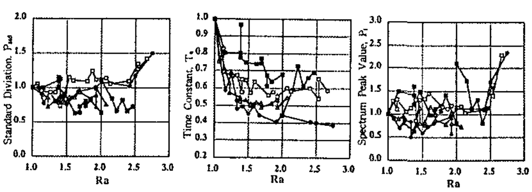

Fig. 8 Comparison of Three Parameters for the Surface Roughness

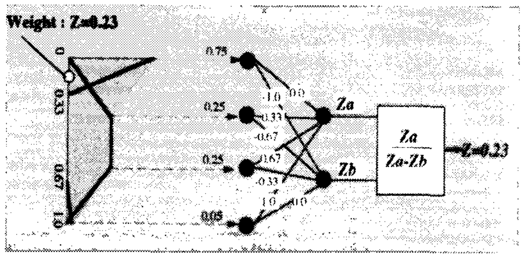

Fig. 9 Obtaining Method for the Neuro · Fuzzy Inference Method

Firstly, the premise part (If-clause) carry out the matching by using fuzzy logic on the three input parameters for each data, and then this system can be derived in the inference result represented in the non-fuzzy adopted in the center of weight method by neural network.

Fig. 10 is the pre-estimation value applied in neuro-fuzzy model for each conditions. These results can be seen that rough grinding conditions are smaller than fine grinding conditions for the pre-estimation error. This is known that the high quality density grinding requires a lot of reliability on the pre-estimation model.

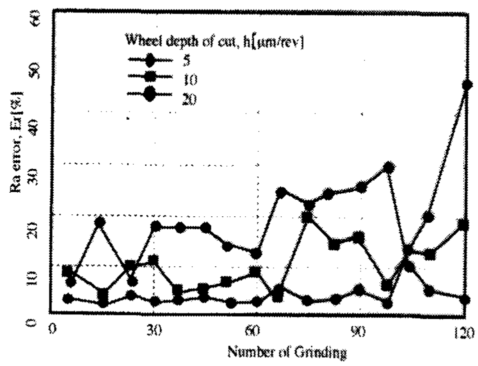

Fig. 10 Estimation Results of Grinding Conditions for Surface Roughness

3.3 Application Results of Regression Model

This result are obtained by regression model for the workpiece surface roughness such that grinding wheel is WA60LmV, wheel velocity is 31.6m/s, workpiece velocity is 0.155, 0.24, 0.37, and 0.62m/s, wheel depth of cut is 2, 4, 6, and 10μ m/rev, and dressing depth of cut is 0.05, 0.03, 0.02mm, dressing feedrate is 0.05, 0.15, and 0.30mm/rev, respectively.

Table 1 Experimental Conditions

Parameter	Conditions
Grinding wheel	WA60LmV
Wheel velocity(m/s)	0.16, 0.24, 0.37, 0.62
Depth of cut(μ m/rev)	2, 4, 6, 10
Dressing depth of cut(mm)	0.02, 0.03, 0.05
Dressing feedrate(mm/rev)	0.05, 0.15, 0.30

In this result it can be obtained as the experimental equation given in coefficient β i and instant integer α , the experimental co-relationship is γ =0.836 and determine coefficient is D=0.698. Therefore, these results are summarized as equation (19).

$$R_a=e^{4.223} \cdot V_w^{-1.419} \cdot h^{0.629} \cdot t_d^{24.458} \cdot f_d^{7.024} \qquad (19)$$

The equation (19) can be replaced on the equation (20) represented a linear regression model by means of transferring a common logarithmic equation both sides. The obtained the linear regression model as follows:

$$\begin{aligned} lnR_a &= 4.223-1.419\ lnV_w \\ &+ 0.629\ lnh + 24.458\ lnt_d + 7.024\ lnf_d \end{aligned} \qquad (20)$$

As given in equation (20), it is known that the pre-estimation model on workpiece surface model according to grinding conditions is some effected on the time function of grinding operations. However, the system has a strongly reliability such that the composition of grinding operation on the independable parameter is constructed with workpiece velocity Vw, depth of cut h, dressing depth of cut td, and dressing lead fd.

This means that grinding wheel velocity has no regard as the independable parameter since the maximum wheel velocity is effected in the grinding efficiency[4]. But, the suggested regression model may be utilized with data file according to kind of grinding wheel since grinding wheel condition is fixed.

On the other hand, Fig. 11 indicates the results according to grinding time comparison of between regression model and neuro-fuzzy model for experimental data and pre-estimation result. As shown in the results, it is known that the neuro-fuzzy model is more reliability than the conventional regression model.

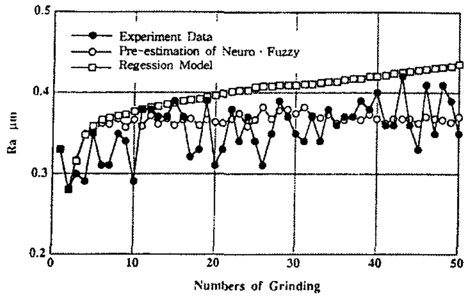

Fig. 11 Comparison of Pre-estimation Surface Roughness for Regression and Neuro-Fuzzy Model

However, this model must be compared with several experimental conditions for more effective construction of pre-estimation model.

4. Conclusions

In order to achieve this purpose, it is necessary to administer the tool life of grinding wheel and to optimize grinding conditions. On the other hand, grinding with a worn wheel causes the workpiece surface roughness to increase and often results in the occurrence of such troubles as chatter vibration and burning. Grinding efficiency and accuracy are affected upon the geometric shape of wheel, and it is difficult to determine it rationally because of the need of much experience.

In this study, grinding power is applied to estimate to monitoring of grinding process for pre-estimating workpiece surface roughness. The results obtained through the present study are summarized as follows.

1) A neural network is applied to estimate the workpiece surface roughness.

2) Fuzzy-neuro is applied to optimize grinding cycle. Observation and analysis of grinding power signal, management of optimization and so forth are made a problem of CNC programs are communicated with machine tool. Most of production process is automated through the computer control.

3) Grinding cycle is optimized for purpose of shorting the grinding time of process and control surface roughness of workpiece suitably. And the effect is evidenced by experiments of process.

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