Global Jour. of Engg. & Tech.
Volume 1, Number 2 (2008) 153-159

A NEURO–FUZZY APPROACH TO GRINDING PROCESS CONTROL

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Abstract : Grinding is one of the most important finishing operations and it is very useful in our automobile industries. The paper presents,a control system for grinding process using neuro–fuzzy technique. The maximum grinding temperature is very important since too high temperature will lead to surface burns snd thermal damage to the grinding wheel as well as the workpiece material. Neuro–fuzzy model was used to analyze the grinding wheel performance index as it affects the general grinding operations of the grinding process. The research work can be applied to any other grinding process, whether it is a wet or dry grinding process. However, the work is new as it appears to be the first application of neuro–fuzzy grinding operations.

1. Introduction

Grinding is one of the most versatile methods of removing material from machine parts by the cutting action of the countless hard and sharp abrasive particles of a revolving grinding wheel to provide precise geometry. Grinding or abrasive machining therefore, refers to processes for removing material in the form of small chips by the mechanical action of irregularly shaped abrasive grains that are held in place by a bonding material on a moving wheel or abrasive belt. (Diniz et al 2000). The grinding wheel is made of very small, sharp and hard abrasive particles or grits held together by strong porous bond and during grinding, a small tiny chip is cut by each of these active grains that comes in contact with the work piece as the grinding wheel whirls past it (Odior, 2002) The size of the chip being cut by each microscopic active grain is so small that it is less than 1 micrometer which is on a nano scale.

The temperature reached by the tip of the abrasive particles when cutting is extremely high and higher than the melting point of steel which is 1,500°C. However, no melting of grains occurs due to brief time of contact, which is often less than 100×10^{-6} sec. (Radford, et al. 1978). The different depths of cut on work piece deformation had been discovered to affect the hardness of the abrasive wheel. (Crawford, 1979). However, the most generally recognized characteristic wheel hardness is the ability of the wheel to retain dulled abrasive grains. The duller the retained grains, the harder the wheel.

Keywords : Grinding Process, Finishing Operation, Thermal Damage, Neuro—Fuzzy.

A neuro–fuzzy model combines the fuzzy–logic and neural network principles to generate model that will result in the evaluation of specified desired output. While fuzzy logic performs an inference mechanism under cognitive uncertainty (Zadeh, 1988), computational neural networks offer exciting advantages, such as learning, adaptation, fault-tolerance, parallelism and generalization (Wasserman, 1989). To enable a system to deal with cognitive uncertainties in a manner more like humans, we incorporate the concept of fuzzy logic into neural networks to evaluate the performance characteristics of a grinding wheel and the resulting hybrid system is called fuzzy neural, neural fuzzy, neuro-fuzzy or fuzzy-neuro network.

Grinding operation is complex since it is characterize by a number of design parameters and variables such as grindability of workpiece material, particle size distribution, material hold–up, rotational speed of the grinding wheel and workpiece speed, (Li, et,al 2005). Conventional grinding is characterized by grinding with small depth of cut and high work speed. The grinding processes consist of three stages : sliding stage, plow stage and chip–formation state. These stages are energy consuming with the corresponding specific grinding energy (U) consisting of sliding energy (U_{sl}), plow energy (U_{pl}) and chip–formation energy (U_{ch}).

MAXIMUM GRINDING TEMPERATURE

The grinding parameters of evaluation the maximum acceptable grinding temperature include, circumferential speed of a grinding segment (v_s), workpiece velocity (v_w) and work depth of cut (a). The circumferential speed of a grinding segment (v_s) is close to constant for a grinding machine for tool (Malkin and Ritter 1989). The parameters of workpiece velocity (v_w) and depth of cut (a) are input parameters of the grinding process, so they are outputs of the fuzzy controller. Therefore, two grinding parameters are obtained by fuzzy controller at time t, and are defined by $U_1(a, \delta_1)$ and $U_2(v_w, \delta_2)$ at this moment.

The empirical formula for maximum grinding tempereature is (Malkin, 1989),

$$Q_m = \frac{1.13\alpha^{0.5}a^{0.75}v_w^{0.5}(u - 0\cdot 45u_{ch})}{kd_e^{0.25}} \qquad \text{... (1)}$$

Where Q_m = the maximum temperature
α = the thermal conductivity,
a = the depth of grinding, v_w = the workpiece velocity,
u = the specific grinding energy, u_{ch} = the chip-formation energy.
k = the thermal diffusivity,
d = the equivalent wheel diameter.

We define $U = (u - 0\cdot 45u_{ch})$, so U, α, k are unknown parameters needed to be estimated. Taking the natural logarithm of both sides of equation 1 above, we have ;

$$\text{In } Q_m = \text{In}\left(\frac{1.13\alpha^{0.5}a^{0.75}v^{0.5}U}{kd_e^{0.25}}\right) \qquad \text{... (2)}$$

$$\therefore \text{ In } Q_m - \text{In}\left(\frac{1.13\alpha^{0.5}a^{0.75}v_w^{0.5}}{d_e^{0.25}}\right) = 0.5 \text{ In } \alpha + \text{In } U - \text{In } k \qquad \text{... (3)}$$

Assume $Y = \text{In}\dfrac{Q_m d_e^{0.5}}{1.13a^{0.75}v^{0.5}}$, $\varphi = (0.5\ 1 - 1)$ and $x = (\text{In}\alpha\ \text{In}U\ \text{In}k)^T$,

Equation 3 can be written in the form $Y = \Phi x$ ... (4)

According to the theorem of Recursive least-squares estimation (RLS), we have ;

$x_{N+1} = x_n + k_{N+1}(y_{N+1} - \varphi^T_{N+1}\theta_N)$ ..... (5)

$k_{N+1} = P_N\varphi_{N+1}(1+\varphi^T_{N+1}P_N\varphi_{N+1})^{-1}$ ..... (6)

$P_{N+1} = P_N - P_N\varphi_{N+1}(1+\varphi^T_{N+1}P_N\varphi_{N+1})^{-1}\varphi^T_{N+1}P_N$ ..... (7)

in above formulae $\varphi^T_{N+1} = (0{\cdot}5 \;\; 1-1)$, $P_N = [\Phi^T, \Phi]^{-1}$. In this way, we can obtain the estimation at time t :)

$$x_t = (\ln \alpha_t \;\; \ln U_t \;\; \ln k_t)^T \text{ ..... (8)}$$

Then with x_t estimated by above formulae and defining $Q_m = T°C$,

where T°C is the given temperature for avoiding workpiece distortion in the grinding process.

Hence we can develop the following equation :

$$\frac{1.13\alpha_t^{0.5} d^{0.75} v_w^{0.5}(u-0.45u_{ch})_t}{k_t d_e^{0.25}} \le T^\circ C,$$

which can be further expressed as : $d^{0.75}v_w^{0.5} \le \dfrac{k_t d_e^{0.25}}{1.13\alpha_t^{0.5}(u-0.45u_{ch})_t} T^\circ C = A_t$ ... (9)

This implies that we should maximize the metal removal rate (MRR) without subjecting the grinding process to over – heating and distortion while the machine is working with efficiency as high as possible.

But MRR = bav_w .... (10)

where b is the width of wheel.

We need to maximize the metal removal rate at an acceptable temperature level.

The control of above equation becomes ;

MRR = $\max|Bav_w|$ .... (11)

Such that ; $a^{0.75}v_w^{0.5} \le A_t$ .... (12)

s.t. $a \in U_1(a, \delta_1)$ .... (13)

s.t. $v_w \in U_2(v_w, \delta_2)$ .... (14)

Solving above equations (3.11 – 3.14) gives the control laws as follows :

$v_w \le At^2 a_t^{-3/2}$ .... (15)

where $a_t = \min\{a \in U_t(a, \delta_t)\}$.

We reduce the control law $v_w \le At^2 a_t^{-3/2}$ to the form $V^* \le A^* a^*$ for the neuro – fuzzy model.

where $V^* = v_w$, $A^* = A_t^2$ and $a^* = a_t^{-3/2}$.

The model gives three sets of conditions :

(1) $V^* - A^*a^* = 0$

(2) $V^* - A^*a^* \ge 0$

(3) $V^* - A^*a^* \le 0$

Considering the output parameters from the model, we have the following

(i) $V^* - A^*a^*$ = Zero (Z) = Optimistic (O_p)

(ii) $V^* - A^*a^*$ = Negative (N) = Normal (N)

(iii) $V^* - A^*a^*$ = Positive (P) = Pessimistic (P_e)

The neuro – fuzzy model recognizes the above output parameters as input parameters and then process them to arrive at the specified desired output of maximum metal removal rate at acceptable temperature level in the grinding process.

The neuro – fuzzy model structure is now given in Figure-1. It should be noted that X_1, X_2, X_3, represent input parameters, layers 1, 2, 3 and N_1, N_2, N_3 and N_4 represent connections between the input and output parameters, while y_1, y_2, y_3 represent the output parameters and y_d represent the desired output.

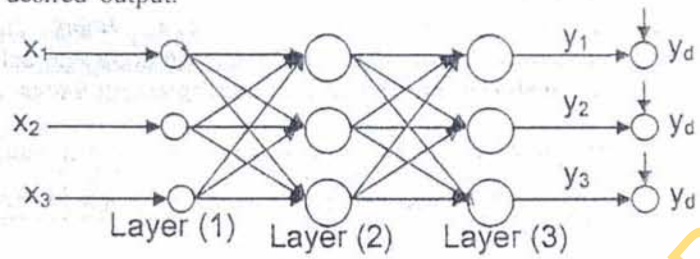

Fig. 1 : The Structure of a Neuro – Fuzzy Model.

The neuro-fuzzy model in Figure 1 is now reduced to the following form for simplicity.

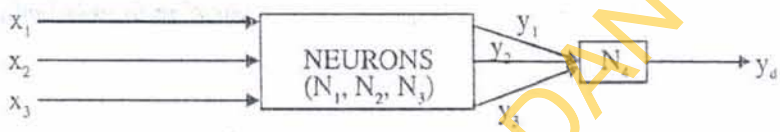

Fig. 2 : A Simplified Layout of Neuro – Fuzzy Model.

To process the parameters to arrive at the specified desired output, the following base rules are employed ;

(1) IF $(V^* - A^*a^*) = Z$, AND $(V^* - A^*a^*) = Z$ continues, THEN output = O_p.

(2) IF $(V^* - A^*a^*) = N$, AND $(V^* - A^*a^*) = N$ continues, THEN output = Nil.

(3) IF $(V^* - A^*a^*) = P_e$, AND $(V^* - A^*a^*) = P_e$ continues, THEN output = Nil.

Our desired output is O_p, a condition of optimistic, where the metal removal rate is maximized at an acceptable temperature level.

3.4 : PERFORMANCE INDEX OF A GRINDING WHEEL.

The performance index used to characterize wheel wear resistance is the wheel grinding ratio or G ratio and is defined as the ratio of the change in volume of the workpiece ground (ΔV_w), to the change in the volume of the grinding wheel removed (ΔV_e), and is expressed as

$$G = \frac{\Delta V_w}{\Delta V_e} \qquad \text{.... (16)}$$

It should be noted that a very high grinding ratio (G) is desirable for high grinding efficiency and this means that grinding ratio should be much, much greater than one.

ie G >>>>>1.

Figure-3 shows the components of grinding wheel performance index for high grinding efficiency.

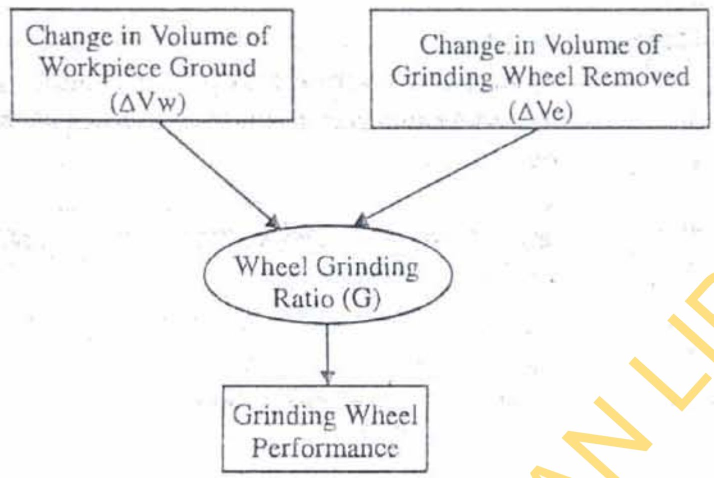

Fig. 3 : Component of Grinding Wheel Performance Index

Three conditions are apparent is this case ;

(1) G > 1 ie $\frac{\Delta V_w}{\Delta V_e} > 1$ which is desirable.

(2) G = 1 ie $\frac{\Delta V_w}{\Delta V_e} = 1$ which is normal.

(3) G < 1 ie $\frac{\Delta V_w}{\Delta V_e} < 1$ which is not desirable.

Considering the output parameters from the model, we have the follow conditions :

(1) $\frac{\Delta V_w}{\Delta V_e} > 1$ = High (H) = Optimistic (O_p).

(2) $\frac{\Delta V_w}{\Delta V_e} = 1$ = Normal (N) = Normal (N).

(3) $\frac{\Delta V_w}{\Delta V_e} < 1$ = Low (L) = Pessimistic (P_e).

The neuro-fuzzy model is now used for the above parameters and the model recognizes the above output parameters as input parameters, which are processed to arrive at the specified desired output of high grinding efficiency, which consists of very high volume of workpiece material removed with very low volume of grinding wheel material removed.

In other to process the above parameters to arrive at the specified desired output, the following base rule are employed :

(1) $(\Delta V_w - \Delta V_e)$ = Positive (P) = High (H) = Optimistic (O_p).
(2) $(\Delta V_w - \Delta V_e)$ = Zero (Z) = Normal (N) = Normal (N).
(3) $(\Delta V_w - \Delta V_e)$ = Negative (N) = Low (L) = Pessimistic (P_e).

So we have the following results :

(1) IF $(\Delta V_w - \Delta V_e)$ = P AND $(\Delta V_w - \Delta V_e)$ = P continues, THEN output O_p.

(2) IF $(\Delta V_w - \Delta V_e)$ = Z AND $(\Delta V_w - \Delta V_e)$ = N continues, THEN output Nil.

(3) IF $(\Delta V_w - \Delta V_e)$ = N AND $(\Delta V_w - \Delta V_e)$ = L continues, THEN output Nil.

Our desired output is O_p a condition of optimistic, where the change in volume of workpiece material removed is higher than that of the grinding wheel material removed.

The specified desired output of high grinding efficiency is not for just a high grinding ratio but for a very high grinding ratio. In this case, we need to have the following output parameters :

(1) $(\Delta V_w - \Delta V_e) >>>> 1$ = Very High Positive (VHP).

(2) $(\Delta V_w - \Delta V_e) = 0$ = Very High Normal (VHN).

(3) $(\Delta V_w - \Delta V_e) <<<< 1$ = Very Low Negative (VLN).

So we have the following results :

(1) $(\Delta V_w - \Delta V_e)$ = P. = Very High Positive (VHP) = Optimistic (O_p) ;

(2) $(\Delta V_w - \Delta V_e)$ = Z = Very High Normal (VHN) = Most Likely (M_l) ;

(3) $(\Delta V_w - \Delta V_e)$ = N. = Very Low Negative (VLN) = Pessimistic (P_e).

3.4.1 : The Components of Fuzzy Logic Model.

The components of the fuzzy logic control model of the grinding wheel performance index can now be represented with membership functions as presented in Table 1.

Table 1 : Components of Fuzzy Logic Model.

Level Number	Interpretation	Fuzzy Output	Linguistic Variables
1	Pessimistic	Negative	$(\Delta V_w - \Delta V_e)$
2	Most Likely	Zero	$(\Delta V_w - \Delta V_e)$
3	Optimistic	Positive	$(\Delta V_w - \Delta V_e)$

The neuro – fuzzy model now uses the following output parameters as input parameters to arrive at the specified desired output.

(1) IF $(\Delta V_w - \Delta V_e)$ = P AND $(\Delta V_w - \Delta V_e)$ = VHP continues, THEN output O_p.

(2) IF $(\Delta V_w - \Delta V_e)$ = Z AND $(\Delta V_w - \Delta V_e)$ = VHN continues, THEN output Nil.

(3) IF $(\Delta V_w - \Delta V_e)$ = N AND $(\Delta V_w - \Delta V_e)$ = VLN continues, THEN output Nil.

3.4.2 : Grinding Wheel System Operating Rules.

INPUT No 1 : {"Input", Positive (O_p), Negative (P_e), Zero (N)}.

INPUT No. 2 {GP – Getting Positive (O_p), GN-Getting Negative (P_e), GZ-Getting Zero (N)}.

The system response with its output becomes :

Output O_p = Optimistic, P_e = Nil, and N = Nil.

The degree of relationship between fuzzy output and membership function ranges from 0 to 1.0. The graphical illustration of Table-1 is presented in Figure-2.

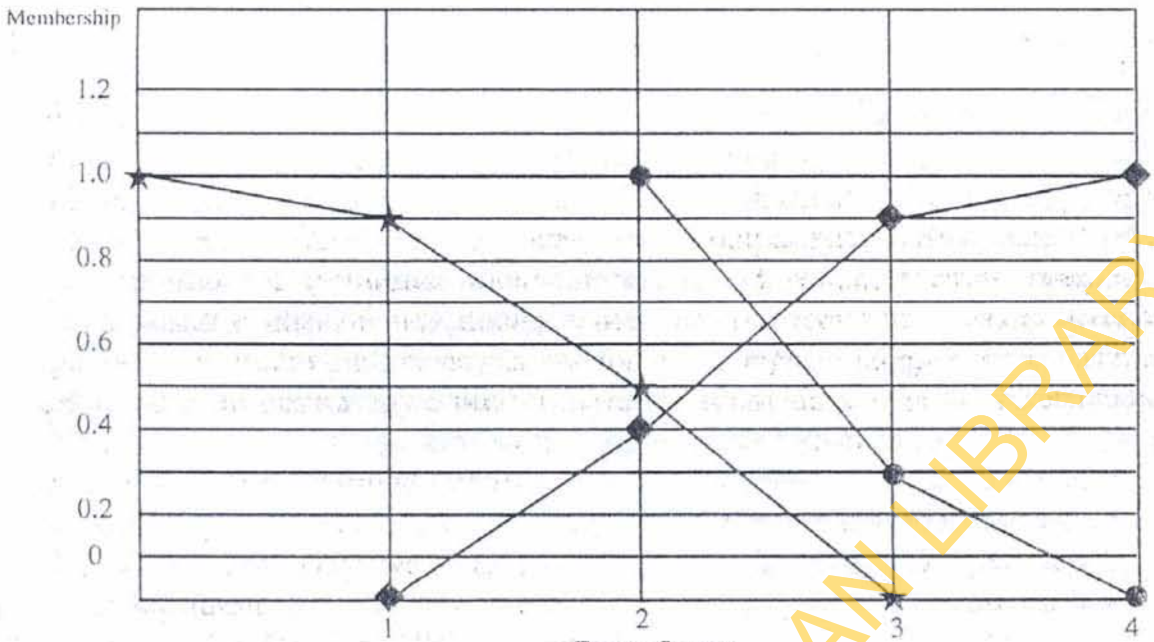

Figure 2 : Graph. of Fuzzy Logic Control Model

The interpretation of the graph shows that :

i. When the change in volume of workpiece ground is higher than the change in volume of grinding wheel removed the model prompts positive (optimistic output)

ii. When the change in volume of workpiece ground is lower than the change in volume of grinding wheel removed the model prompts negative (pessimistic output) ; and

iii. When the chnage in volume of workpiece ground and the chnage in volume of grinding wheel removed are equal the model prompts zero (Most Likely output)

CONCLUSION

Grinding is one of the most versatile methods of removing from machine parts by abrasion. It is an important finishing operation which is very useful in our automible industries. As a result of the complexity of grinding operation, it was more convenient to use neuro fuzzy models to control the grinding process. The process was carefully controlled to get the desired output with maximum metal removal rate at an acceptable temperature level that will not lead to workpiece burns. Also the performance index which characterizes the wheel wear resistance was also modeled and it was discovered that the wheel grinding ratio should always be very high for effective control of the grinding process.

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