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Application of Neuro-Fuzzy Models to Grinding Wheel Parameters

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Abstract

Grinding is one of the most important finishing operations and it is very useful in our automobile industries. A grinding wheel is made of very small, sharp and hard abrasive particles or grits held together by strong porous bond. The paper presents, a control system for grinding process using neuro – fuzzy technique. The grinding parameters include circumferential speed of a grinding segment workpiece velocity and work depth of cut. The maximum grinding temperature is very important since too high temperature will lead to surface burns and thermal damage to the grinding wheel as well as the workpiece material. For fuzzy modeling, all the numerical values are replaced with linguistic values. The research work can be applied to any other grinding process, whether it is a wet or dry grinding process.

Introduction

A grinding wheel is an expendable wheel that carries an abrasive compound on its periphery. They are made of small, sharp and very hard natural or synthetic abrasive minerals, bonded together in a matrix to form a wheel. Each abrasive grain is a cutting edge and as the grain passes over the workpiece, it cuts a small chip, leaving a smooth, accurate surface. As the abrasive grain becomes dull, it breaks away from the bonding material exposing new sharp grains (Odior and Oyawale, 2008a). The abrasive particles or grits are 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. 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, (Odior and Oyawale, 2008b).

Abrasive materials for grinding are classified into two groups: natural and synthetic abrasive materials. Natural abrasive materials are those materials that are found existing naturally and among the important natural abrasive materials include; aluminosilicate mineral, feldspar, calcined clays, lime, chalk and silica, flint, kaolinite, diatomite and diamond, which is the hardest known natural material, (Brecker, 2006). The use of natural abrasive materials goes back to early man who used them to sharpen his tools. Early man shaped weapons and tools by rubbing them against hard and rough stone. Pictographs also show ancient Egyptians using natural abrasive stones to polish pottery and jewelry (Scott, 2010). Abrasive stones have been used for ages to clean and sharpen everything from weapons and tools, and even for cleaning the decks of English navy ships. The earliest form of sandpaper would have been loose sand held in flexible bits of leather or rawhide. Crude adhesives were later used to attach abrasive grit to flexible backings (Scott, 2010). Impurities in the natural abrasive materials make them less effective. As a result of this and with advancement in technology, man began to search for better alternative abrasive materials and the search led to the discovery of synthetic abrasive material by Acheson in 1891.

Synthetic abrasive materials are those abrasive materials that are usually manufactured, and their qualities and compositions can easily be controlled. An important characteristic of the synthetic abrasive materials is their purity which has an important bearing in their efficiency (Arunachalam and Ramamoorthy, 2007). The most commonly used synthetic abrasive materials include silicon carbide, aluminium oxide, Cubic Boron Nitride (CBN), while aluminium oxide and silicon carbide are the most common mineral in use today, (Zhong and Venkatesh, 2008). The Cubic Boron Nitride (CBN) shows a great promise in the grinding of high speed steels and its hardness approaches that of diamond. The various grades of each type of synthetic abrasives are distinguishable by properties such as colour, toughness, hardness and friability and the differences in properties are caused by variation in purity of materials and method of processing.

The art of grinding dates back many centuries, since man first discovered that he could brighten up and sharpen his tools by rubbing them against certain stones or by plunging them into sand several times. The emery stone appeared when man found that the softer sand stone did not work well on the newly discovered harder materials, (Salmon, 1992). By the early nineteenth century, emery (a natural mineral containing iron and corundum) was used to cut and shape metals. Acheson discovered silicon carbide in 1891, while he was attempting to manufacture precious gems in an electric furnace, and a few years later, Jacob developed aluminium oxide from claylike mineral bauxite. Also, in 1897, Pulson made the first grinding wheel by combining emery with potter's clay and firing it in a kiln. He noted that emery was a natural abrasive of non-uniform texture, so its quality as a grinding wheel varied greatly (Salmon, 1992). However, emery's variable quality and problems with importing it from India prior to its discovery in the United States prompted efforts to find a more reliable abrasive mineral. By the 1890s, the search had yielded silicon carbide, a synthetic abrasive mineral harder than corundum, (Theodore, (2009).

Grinding operation is complex since it is characterized 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 stage. 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}). 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 and Richardson, 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.

Fuzzy set theory provides a remedy for any lack of uncertainty in the data, (Jagannath *et al.*, 2007) while an artificial Neural Network can capture the relationship between input and output by adjusting weights on each link while learning from data and they are becoming more useful in the areas of pattern recognition and prediction (Osofisan .and Afunlehin, 2007). Therefore, selection of data pairs of input and output for training the network is an essential step to ensure sufficiency and integrity of the target function (Siwaporn, 2007). Attempts to blend two artificial intelligence techniques have been made in the process of solving problems like fuzzy system identification based on input-output data and fuzzy controller parameters tuning (Benachaiba *et al.* 2006). To enable a system to deal with cognitive uncertainties in a manner more like humans, one may incorporate the concept of fuzzy logic into neural networks, (Barai and Nair, 2004). 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.

The Structural Composition of a Grinding Wheel

A grinding wheel consists of abrasive grains (A_bG_r), the bonding material (B_oM_a), and the pore (P_o). Therefore the structure of a grinding wheel is the relationship of the abrasive grain to the bonding material and the relationship of these two elements to the spaces or voids that separate them. A grinding wheel consists of abrasive grains (A_bG_r), the bonding material (B_oM_a), and the pore (P_o). A grinding wheel is made with the proportions of three major components, (Malkin and Ritter, 1989) as follows:

$$G_w = P_g + P_b + P_p = 1.0$$

Where P_g – volumetric proportion of grains;

P_b = volumetric proportion of bonding material;

and P_p = volumetric proportion of pores.

$$\text{So, } G_w = P_g + P_b + P_p, \quad \text{and } P_g + P_b + P_p = 1.0 \qquad (1)$$

A neural network is now used for a typical grinding wheel as follows,

$$\sum_{i}^{N} P_i W_i > 0$$

or

$$\sum_{i}^{N} P_i W_i \le 0 \qquad (2)$$

where W = weight, i = g, b, p and N = 1 to 3.

The model gives the following two different types of outputs:

output #1 = 1 if $W_g P_g + W_b P_b + W_p P_p > 0$

output #2 = 0 if $W_g P_g + W_b P_b + W_p P_p \le 0$

Therefore; for $W_g P_g + W_b P_b + W_p P_p > 0$, output = 1

And for if $W_g P_g + W_b P_b + W_p P_p \le 0$, output = 0.

The network adapts as follows:

Change the weight by an amount proportional to the difference between the desired output and the actual output. This leads to the following equation;

$$\Delta W_i = \eta * (D - Y) \cdot P_i; \qquad (3)$$

where η is the learning rate,

D is the desired output

and Y is the actual output.

Since only two components; the grain and the bond are the major constituents of a grinding wheel, the neuro fuzzy model reduces to :

$$\{W_g P_g + W_b P_b + W_p\}^{>0}_{\le 0} \qquad (4)$$

The neural network is given in Figure 1, while the output from the model becomes:

1. output #1 = 1 if $W_g P_g + W_b P_b + W_p > 0$
2. output #2 = 0 if $W_g P_g + W_b P_b + W_p \le 0$. (5)

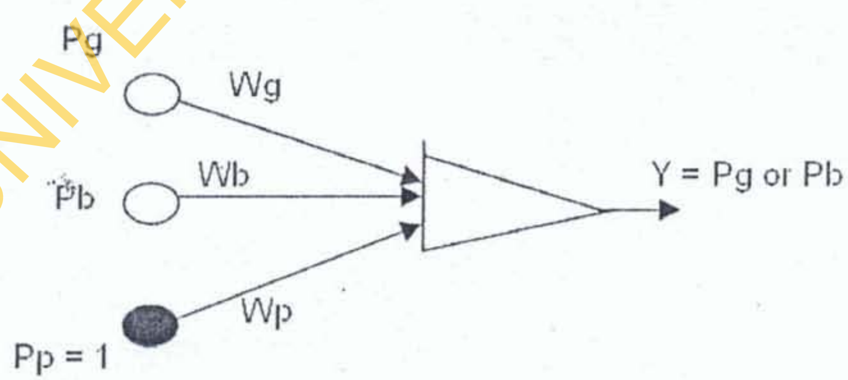

Figure 1: The Neural Network for the Grinding Wheel Components.

The components of the neural network model with the desired outputs are now presented in Table 1 below:

Table 1: The Inputs and the Desired Output from the Neuro - fuzzy Model.

INPUTS		DESIRED OUTPUT
Grain (P_g)	Bond Material (P_b)	
0	0	0
0	1	1
1	0	1
1	1	1

The Membership Function for the Abrasive Grain Size and Wheel Grade.

The membership function for the abrasive grain size is given in Figure 3.12, while the membership function for wheel grade is presented in Figure 3.13.

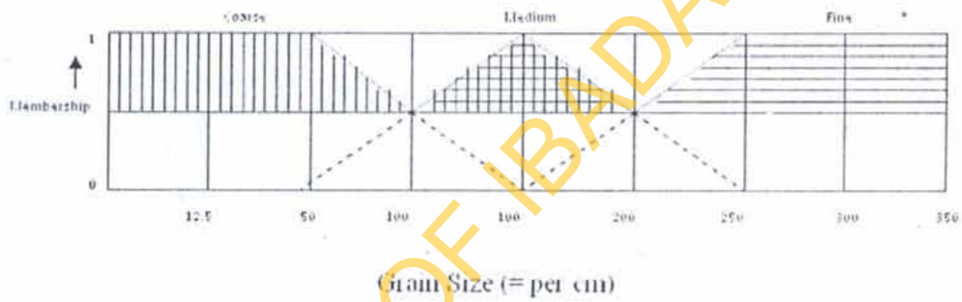

Figure 2: Membership Function for Grain Size.

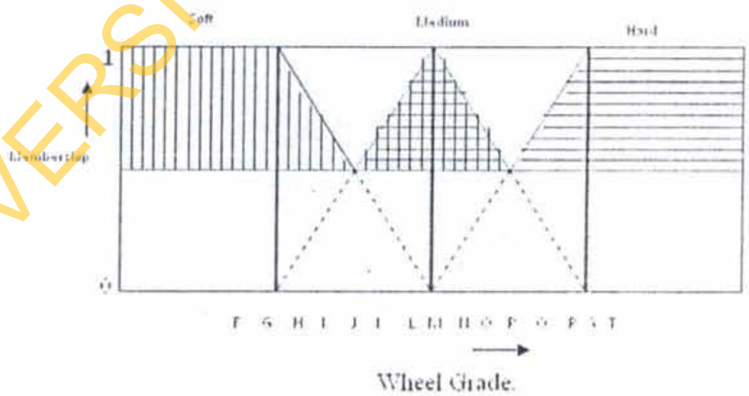

Figure 3: Membership Function for Wheel Grade.

Maximum Grinding Temperature

The grinding parameters for evaluating 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 temperature is (Malkin and Ritter, 1989),

$$Q_m = \frac{1.13\alpha^{0.5}a^{0.75}v_w^{0.5}(u-0.45u_{ch})}{kd_e^{0.25}} \tag{6}$$

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 $U = (u - 0.45u_{ch})$, so U, α, k are unknown parameters needed to be estimated.

Taking the natural logarithm of both sides of equation (6) above, we have;

$$\ln Q_m = \ln\left(\frac{1.13\alpha^{0.5}a^{0.75}v^{0.5}U}{kd_e^{0.25}}\right) \tag{7}$$

$$\therefore \ \ln Q_m - \ln\left(\frac{1.13a^{0.75}v_w^{0.5}}{d_e^{0.25}}\right) = 0.5\ln\alpha + \ln U - \ln k \tag{8}$$

Assume $Y = \ln\frac{Q_m d_e^{0.25}}{1.13a^{0.75}v^{0.5}}$, $\varphi = (0.5 \ \ 1 \ \ -1)$ and $x = (\ln\alpha \ \ \ln U \ \ \ln k)^T$,

Equation 3 can be written in the form $Y = \Phi x$ (9)

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

$$x_{N+1} = x_N + k_{N+1}(y_{N+1} - \varphi_{N+1}^T\theta_N) \tag{10}$$

$$k_{N+1} = P_N\varphi_{N+1}(1+\varphi_{N+1}^T P_N \varphi_{N+1})^{-1} \tag{11}$$

$$P_{N+1} = P_N - P_N\varphi_{N+1}(1+\varphi_{N+1}^T P_N\varphi_{N+1})^{-1}\varphi_{N+1}^T P_N \tag{12}$$

in above formulae $\varphi_{N+1}^T = (0.5 \ \ 1 \ \ -1)$, $P_N = [\Phi^T, \Phi]^{-1}$. In this way, we can obtain the estimation at time t:)

$$x_t = (\ln\alpha_t \quad \ln U_t \quad \ln k_t)^T \tag{13}$$

Then with x_t estimated by above formulae and defining $Q_m = T^oC$, where T^oC is the given temperature for avoiding workpiece distortion in the grinding process.

Hence we can develop the following equation:

$$\frac{1.13\alpha_t^{0.5}a^{0.75}v_w^{0.5}(u-0.45u_{ch})_t}{k_t d_e^{0.25}} \le T^oC, \qquad (14)$$

which can be further expressed as:

$$a^{0.75}v_w^{0.5} \le \frac{k_t d_e^{0.25}}{1.13\alpha_t^{0.5}(u-0.45u_{ch})_t}T^oC = \Lambda_t \qquad (15)$$

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 $MRR = bav_w$ 16

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;

$MRR = \max|Bav_w|$ 17

Such that; $a^{0.75}v_w^{0.5} < A_t$ 18

s.t. $a \in U_1(a,\delta_1)$ 19

s.t. $v_w \in U_2(v_w,\delta_2)$ 20

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

$v_w \le A_t^2 a_t^{-3/2}$ 21

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

We reduce the control law $v_w \le A_t^2 a_t^{-3/2}$ 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

1. $V^* - A^*a^* =$ Zero (Z) = Optimistic (O_p)
2. $V^* - A^*a^* =$ Negative (N) = Normal (N)
3. $V^* - A^*a^* =$ 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 4..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.

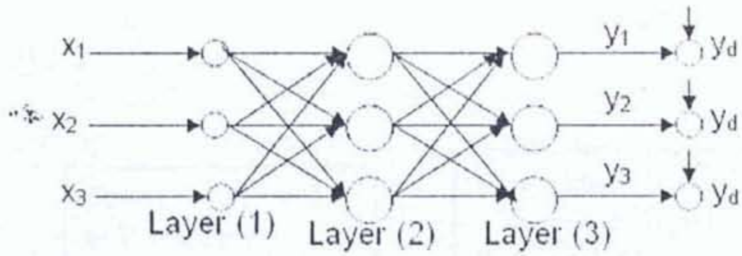

Figure 4: The Structure of a Neuro – Fuzzy Model.

The neuro-fuzzy model in Figure 4 is now reduced to the following form for simplicity.

Figure 5: 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.

Performance Index of a Grinding Wheel

The performance index is 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

$$G = \frac{\Delta V_w}{\Delta V_e} \qquad 22$$

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 6 shows the components of grinding wheel performance index for high grinding efficiency.

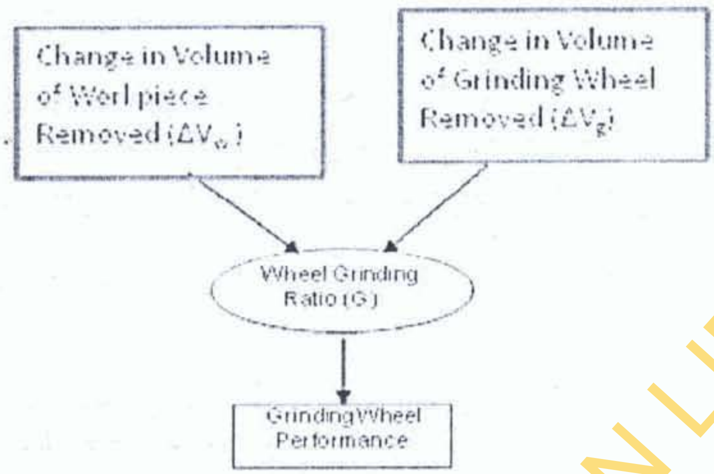

Figure 6: Component of Grinding Wheel Performance Index.

Three conditions are apparent in this case;

1. G >! 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 rules 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).

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 2.

Table 2: 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.

The 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 7.

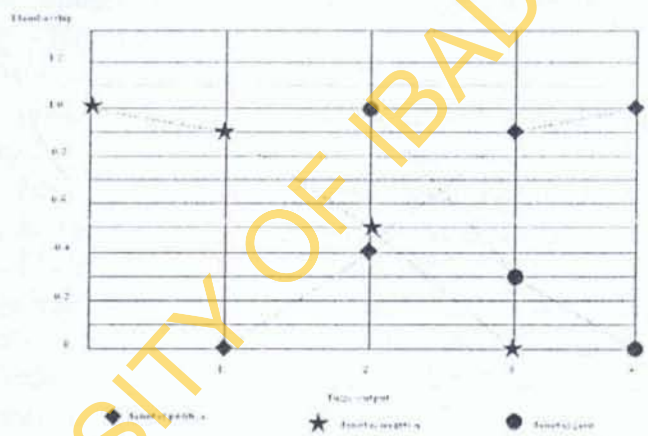

Figure 7: Graph of Fuzzy Logic Control Model.

The interpretation of the graph shows that:

1. 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).
2. 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
3. When the change in volume of workpiece ground and the change 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 material from machine parts by abrasion. It is an important finishing operation which is very useful in industrial and domestic applications. 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 never be less than one for efficient grinding operation and it should always be very high for effective control of the grinding process.

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