The Journal of the Nigerian Institution of Production Engineers

The Journal of the Nigerian Institution of Production Engineers /*Vol. 12, April, 2010, pp.224-232*

A NEURO-FUZZY LINGUISTIC APPROACH TO EXPERIMENTAL PARAMETERS WITH SILICON CARBIDE GRINDING WHEEL

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ABSTRACT

The paper presents a control system for grinding process using fuzzy rule-based model for estimating the grinding conditions at which wheel wears occur. The grinding parameters include circumferential speed of a grinding segment workpiece velocity and work depth of cut using silicon carbide grinding wheels. There was a wide range of applications over many types of mild steel materials and various wheel wear values were recorded for predicting the grinding conditions. Grinding wheels with various wheel hardness grades ranging from soft (H grade) to hard (R grade) and wide range of grit sizes, ranging from coarse to fine.

Keywords: Grinding Parameter, Fuzzy Rule, Silicon Carbide, Grit Size.

1.0 INTRODUCTION

Grinding is one of the most important finishing operations and the loss of abrasive grains from the grinding wheel is undesired but unavoidable (Bhowmick *et al.*, 2006). The basic wear mechanisms that affect most grinding wheels are concerned with grain fracture during metal cutting, fracture of bond bridges, mechanical fracture of abrasive grains due to spalling, and fracture at the interface between abrasive grain and bond bridge (Jackson, 2006a). The inspection and monitoring of the wear of grinding tools is essential to ensure the quality of the grinding tool surface and the finished product (Heger and Pandit, 2004) and the generally accepted parameter of wheel wear is the grinding ratio. However, Oliveira *et al*., (2007) stated that conventionally used grinding ratio is not sufficient to evaluate the wearing condition of the grinding wheel, total judgment considering the variation of wheel surface topography characteristic value is required. The variables affecting the economics of machining operations are numerous and include machine tool capacity, required workpiece geometry, cutting conditions such as speed, feed, and depth of cut, and many others, (Asokan, *et al*., 2005).

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).

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.

A production operation does not require an ''absolute'' model that can deliver high accuracy, because such accuracy is not reproducible in practice. What is needed, as pointed out by Shaw (1996), is a ''relative'' model that can guide the user generally as to what to do and how to do. This is because there will always be a certain degree of on-shop trial-and-error, but a relative model will make a good starting point. This paper aims to address some of these practical concerns, focusing on the prediction of work-piece surface burns, by introducing a simple fuzzy model. The main objective of the model is its practical applicability, such that a machine operator can refer to it from time to time. It should be possible for practicing engineers to use it in process planning, or as part of an intelligent model-reference adaptive controller, without the need for additional information. Moreover, the model should be easy to modify by appending further practical experience. Zadeh's principle of incompatibility (Zadeh, 1973), states that "As the complexity of a system increases, our ability to make precise and yet significant statements about its behaviour diminishes until a threshold is reached beyond which precision and significance (or relevance) become almost mutually exclusive characteristics". In other words, the closer one looks at a real-world problem, the fuzzier its solution becomes. Grinding is truly a complex system, and fuzzy logic techniques may offer a good solution.

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.

2.0 APPROACH TO FUZZY MODELING

A fuzzy model can be viewed as a rule-based expert system with the added benefits from fuzzy sets theory. This theory facilitates the interpolation between, and extrapolation beyond the existing rules. Thus, it overcomes "rule drought" which is one of the drawbacks of conventional expert systems (Ali and Zhang, 2004). For example, when input values do not match exactly any of the input conditions (premises) of the existing rules, a conventional expert system may not fire any rule and may fail to provide any (consequence) output. To overcome this drawback, we will develop a fuzzy model that will fire at least one rule for any set of input values, regardless of the completeness or precision of the values, and will work even in the absence of some of the input values, e.g. with unknown wheel grade or not fully defined coolant composition. This can be realized by disposing of numeric input values altogether and dealing primarily with linguistic values such as ''very large'', ''large'', ''small'', ''extremely small'', etc.

Fuzzy Modeling:

We will develop a fuzzy model that will fire at least one rule for any set of input values, regardless of the completeness or precision of the values. This can be realized by disposing of numeric input values altogether and dealing primarily with linguistic values such as ''very large'', ''large'', ''small'', ''extremely small'', etc (Ali and Zhang, 2004). An extensive set of grinding tests were conducted over a wide range of conditions, and the results were fed into a system that is capable of extracting valid rules from the data.

In the experiments, silicon carbide grinding wheels were used. Various wheel hardness grades, ranging from soft (H grade) to hard (R grade), and a wide range of grit sizes, ranging from coarse (#36) to fine (#120), were tested. This covers many of the possible combinations of wheel grades and grit sizes used in practice.

Grinding tests were performed over a range of cutting depths and work speeds. Cutting depths covered a range in orders of magnitude from 0.1 mm to 10 mm. Work speed also covered a range in orders of magnitude from 1 mm/min to 10 m/min. This wide range includes all grinding conditions from rough grinding form to fine finish grinding The grinding wheels were maintained at a particular surface speed manufacturer (30 m/s).

Establishment of Fuzzy Knowledge Base

For fuzzy modelling, all numeric values are replaced with linguistic values. Dressing is already linguistic (either ''fine'' or ''coarse''), as well as coolant application (''dry,'' ''medium,'' or ''high''). The other numeric variables are fuzzified in a similar manner, by means of membership functions. Fig. 2 shows the Fuzzy membership function for grinding wheel grade. These membership functions help in converting numeric variables into linguistic terms. For example, a grit size 40 can be replaced with coarse/0.5 or medium/0.5.

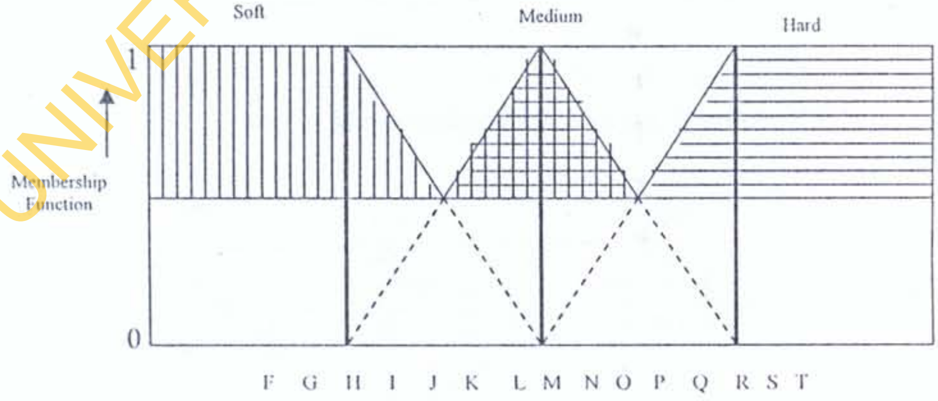

Fig. 1: Membership Functions for Grinding Wheel Grade.

With reference to Fig. 2, this means that: while #20 grit is considered 100% coarse, and #60 grit is 100% medium, #40 grit is considered 50% coarse and 50% medium. Similarly, a 500 mm/min table speed is called (fast/0.7, medium/ 0.3) (note the logarithmic scale).

This transformation is very helpful in interpolating between the rules. For example, no grinding tests were actually conducted using either #40 grit or 500 mm/min table speed. A conventional expert system may not be able to match this input to any of its rules, but the fuzzy model above will respond to this input by firing all rules having coarse or medium grit size and fast or medium table speed. Many rules may fire, with the weight of each rule being the minimum value of all membership values of its premises. The Fuzzy membership function for grinding wheel grit size is presented in Fig. 2 and it illustrates that: while 20 grit is considered 100% coarse, and 60 grit is 100% medium, 40 grit is considered 50% coarse and 50% medium as presented in Figure 2.

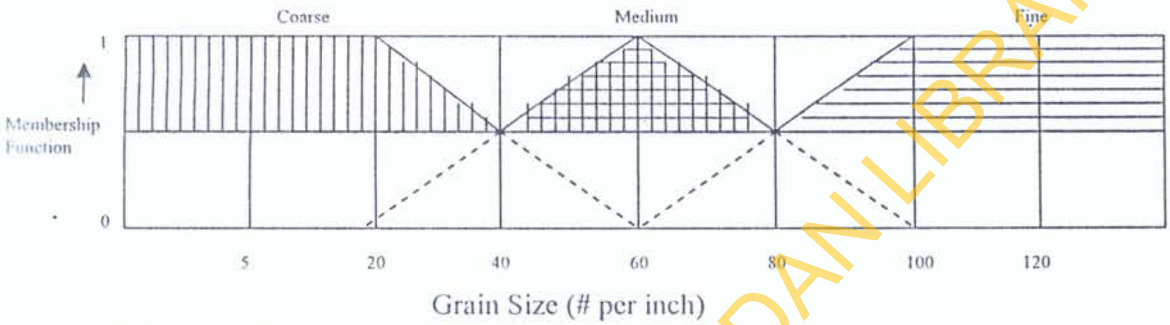

Fig. 2: Membership Functions for Grinding Wheel Grain Size.

Similarly, the membership function for depth of cut is presented in Figure 3, while that of cutting speed is presented in Figure 4. It is noted that a 500 mm/min cutting speed is called (fast/0.7, medium/ 0.3) and this transformation is very helpful in interpolating between the rules.

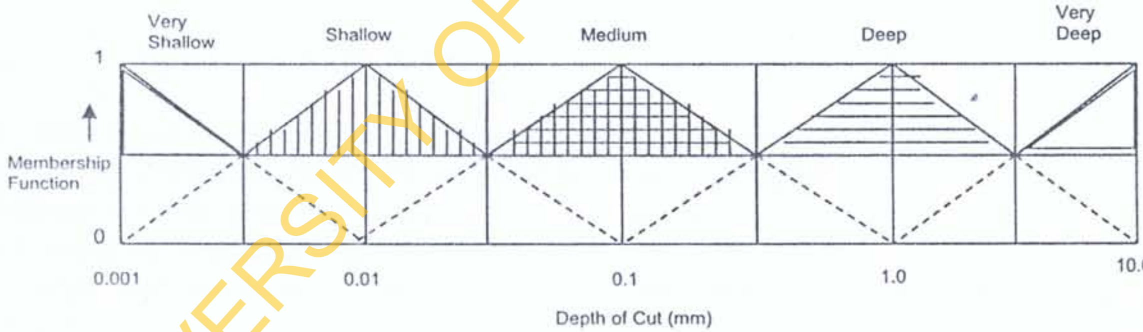

Fig.3: Membership Function for Depth of Cut.

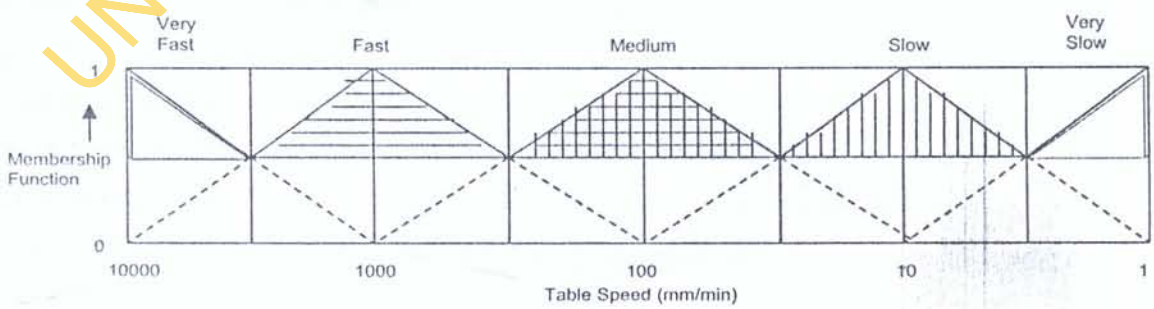

Fig. 4: Membership Functions for Cutting Speed.

3.0 WHEEL WEAR AND WHEEL GRINDING RATIO

Grinding ratios are usually on the order of 5 or higher for ISO wheels to over 60,000 when internally grinding bearing races using cubic boron nitride abrasive wheels (Shih et al. 2003; Jackson, 2006). 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

$$G = \frac{\Delta V_w}{\Delta V_e}.$$

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 $G >>>>> 1$.

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 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	$(\Delta V_w - \Delta V_e)$

Different fine and coarse grinding wheels were used to grind mild steel materials for 15 minutes machining time. The weights of wheels and workpiece were recorded before and after each machining operation and the results were used to estimate the grinding wheel wear and wheel grinding ratios as presented in Tables 2, for fine grinding wheels and Table 3 for coarse grinding wheels.

Table 2: Wheel Wear and Wheel Grinding Ratio for Fine Wheels.

Wheel Sample No.	1	2	3	4	5	6	7	8	9	10	Mean
Wheel Wear	2.07	2.09	2.11	2.09	2.12	2.17	2.20	2.18	2.13	2.22	2.14
Grinding Ratio	28.37	28.98	29.05	28.15	29.25	28.32	29.35	29.35	29.44	29.45	28.97

Table 3: Wheel Wear and Wheel Grinding Ratio for Coarse Wheels.

Wheel Sample No.	1	2	3	4	5	6	7	8	9	10	Mean
Wheel Wear	2.51	2.50	2.52	2.59	2.46	2.66	2.59	2.57	2.58	2.61	2.56
Grinding Ratio	23.37	22.50	24.88	23.90	23.50	22.57	23.07	24.10	23.66	24.12	23.80

The depth of cut, cutting speed, the hardness of material being cut and coolant application were discovered as normal treads which are consistent with the general perception about grinding. The general relative fuzzy rules for avoiding grinding wheel wear and surface burns in grinding are therefore as follows:

1. Softer wheel grade for a hard material,

2. Finer grit size for smooth surface finish,
3. Take a lower depth of cut,
4. Use low cutting speed and
5. Apply much coolant as available.

4.0 CONCLUSION.

Grinding is an important finishing operation which is very useful in industrial and domestic applications. It is one of the most versatile methods of removing material from machine parts by abrasion. Due to 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 low wheel wear and wheel burnt. The mean wheel wear value is 2.14 for fine wheel and 2.56 for coarse wheel while the grinding ratio is 28.97 for fine wheel and 23.80 for coarse wheel. These results show that the wheels are of acceptable standard as the obtained wheel grinding ratiós were always greater than one.

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