A Neuro-Fuzzy Linguistic Approach to Component Elements of a Grinding Wheel

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Abstract

The grinding wheel is made of very small, sharp and hard silicon carbide abrasive particles or grits held together by strong porous bond. These silicon carbide abrasive particles are hard crystalline materials which are held together by a strong, porous bond and these abrasive materials which are of extreme hardness are used to shape other materials by a grinding or abrading action. The paper presents, an analysis of the various component elements of a typical grinding wheel using neuro – fuzzy technique. Among these component elements are, the size of the grains and its spacing, volumetric proportion of grains, volumetric proportion of bonding material and volumetric proportion of pores. However, the work is new as it appears to be the first application of neuro – fuzzy to component elements of a grinding wheel.

Keywords: Silicon Carbide Abrasive, Grinding Wheel, Porous Bond, Neuro – Fuzzy.

1. Heading

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. Grinding wheels are available in a wide variety of sizes, ranging from less than 0.63 centimeter to several meters in diameter. They are also available in numerous shapes like flat disks, cylinders, cups, cones, and wheels with a profile cut into the periphery [1]. The grinding wheel is made of very small, sharp and hard silicon carbide 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 [2]. Those grains at the surface of the wheel that actually perform the cutting operation are called the active grains. As a result of the irregular shapes of the grains, there is considerable interference between each active grain and the new work surface and each active grain actually acts as a single point cutting tool. [3, 4].

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, [5]. A wheel consisting of relatively tough abrasive grains strongly bonded together will only exhibit self sharpening characteristic to a small degree and will quickly develop a glazed appearance during grinding. This glazed appearance is caused by the relatively large worn areas that develop on the active grains and these worn areas result in excessive friction and the overheating of the work piece. It is therefore necessary to dress the grinding wheel at frequent intervals by passing a diamond-tipped dressing tool across the wheel surface while the wheel rotates [6].

A grinding wheel is therefore a complex cutting tool since it is characterized by a number of design parameters and variables which include: the size of the grains and its spacing, volumetric proportion of grains, volumetric proportion of bonding material and volumetric proportion of pores. As a result of the complexity in analyzing the component elements of grinding wheel, a neuro fuzzy approach was adopted for our analysis.

1.1 Neuro-Fuzzy

Neuro-fuzzy system is a combination of neural network and fuzzy logic in which it 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 [7], computational neural networks offer exciting advantages, such as learning, adaptation, fault-tolerance, parallelism and generalization [8]. An example of a neuro-fuzzy system is the adaptive neural network based fuzzy inference system (ANFIS) which combines the Takagi–Sugeno fuzzy inference system (FIS) with neural network. The ANFIS defines five layers which perform the function of fuzzification of the input values,

aggregation of membership degree, evaluation of the bases, normalization of the aggregated membership degree and evaluation of function output values [9]

A typical ANFIS structure with five layers and two inputs, each with two membership functions is shown in Figure1. The five layers of the ANFIS are connected by weights. The first layer is the input layer which receives input data that are mapped into membership functions so as to determine the membership of a given input. The second layer of neurons represents association between input and output, by means of fuzzy rules. In the third layer, the output are normalized and then passed to the fourth layer. The output data are mapped in the fourth layer to give output membership function based on the pre-determined fuzzy rules. The outputs are summed in the fifth layer to give a single valued output. The ANFIS has the constraint that it only supports the Sugeno-type systems of first or 0th order [10]
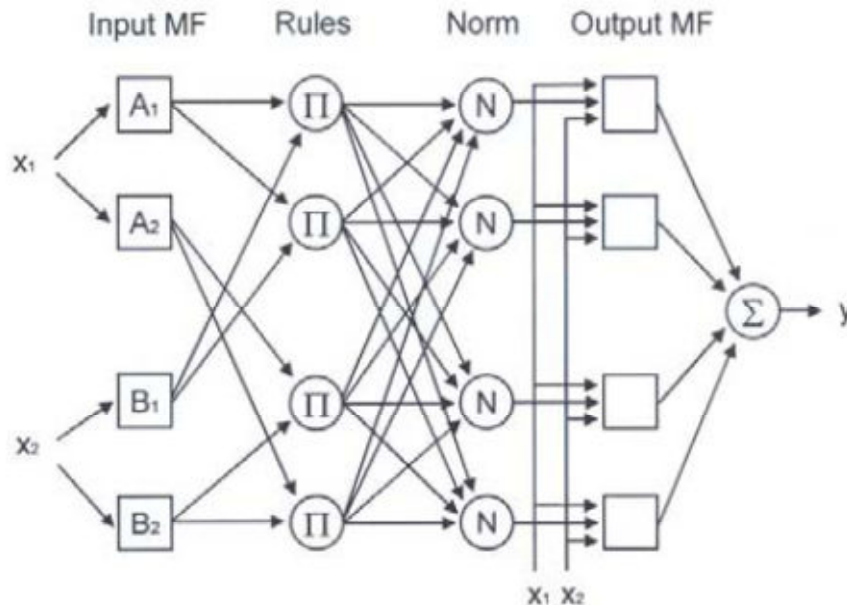

Figure 1: ANFIS structure with 2 inputs, 1 output, and 2 membership function for each input

Fzzy logic [11-13] and artificial neural networks [14, 15] are complementary technologies in the design of intelligent systems. The combination of these two technologies into an integrated system appears to be a promising path toward the development of intelligent systems capable of capturing qualities characterizing the human brain. Neural networks are essentially low-level, computational algorithms that sometimes offer a good performance in pattern recognition and control tasks. On the other hand, fuzzy logic provides a structural framework that uses and exploits those low-level capabilities of neural networks [16]. Both neural networks and fuzzy logic are powerful design techniques that have their strengths and weakness. Neural networks can learn from data sets while fuzzy logic solutions are easy to verify and optimize. Table 1 shows a comparison of the properties of these two technologies. In analyzing this Table, it becomes obvious that a clever combination of the two technologies delivers the best of both worlds [16].

Table 1. Comparison between neural networks and fuzzy inference systems

Artificial Neural Network	**Fuzzy Inference System**
Difficult to use prior rule knowledge	Prior rule-base can be incorporated
Learning from scratch	Cannot learn (linguistic knowledge)
Black box	Interpretable (if-then rules)
Complicated learning algorithms	Simple interpretation and implementation
Difficult to extract knowledge	Knowledge must be available
No mathematical model necessary	Mathematical model necessary

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. 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 as follows [1]:

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

Where P_g = volumetric proportion of grains;

P_b = volumetric proportion of bonding material;

and P_p = volumetric proportion of pores.

So, $G_w = P_g + P_b + P_p$ and

$$P_g + P_b + P_p = 1.0$$

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

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

$$\text{or} \quad \sum_{i}^{N} P_i W_i \leq 0$$

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

The model gives the following two different types of outputs:

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

(2) output #2 = 0 $if \ W_g P_g \ + \ W_b P_b \ + \ W_p P_p \ \leq \ 0$

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

and $for \ W_g P_g \ + \ W_b P_b \ + \ W_p P_p \ \leq \ 0, \ output \ = 0$

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;

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

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 :

$$\left\{ W_g P_g \ + \ W_b P_b \ + \ W_p \right\}_{\leq 0}^{> 0}$$

The neural network is given in Figure 2, while the output from the model becomes:

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

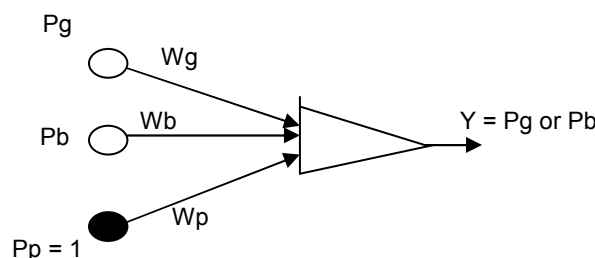(2) output #2 = 0 $if \ W_g P_g \ + \ W_b P_b \ + \ W_p \ \leq \ 0$

Figure 2: The neural network for the grinding wheel components

The components of the neural network model with the desired outputs are now presented in Table 2 below:

Table 2: The Inputs and 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

3. Neuro - Fuzzy Analysis for Abrasive Grains ($A_b g_r$) Production.

The abrasive grains were produced using varying percentages of silica sand ($S_i S_a$),
petroleum coke ($P_e C_o$), saw dust ($S_a D_u$) and common salt ($C_o S_a$). These components were properly mixed for the production. We now develop neuro – fuzzy model for the production of silicon carbide abrasive grains as follows:

$$A_b G_r = S_i S_a + P_e C_o + S_a D_u + C_o S_a$$

3.1 Building the Models from Numerical Values

For fuzzy modeling, all numerical values are replaced with linguistic values that are then used to analyze the model. For example, wheel grade is replaced by the linguistic values; "soft", "medium" or "hard". Therefore, the fuzzy models are built based on the following aspects:

(1)   A very smooth surface finish needs a grinding wheel with finer grit size.
(2)   A smooth surface finish needs a grinding wheel with fine grit size.
(3)   A rough surface finish needs a grinding wheel with coarse grit size.

These parameters are now denoted as follows.

$$Y = A_b G_r = \text{Abrasive Grains,}$$

$$X_1 = S_i S_a = \text{Silicon Sand,}$$

$$X_2 = Pe C_o = \text{Petroleum Coke,}$$

$$X_3 = S_a D_u = \text{Saw Dust,}$$

$$X_4 = C_o S_a = \text{Common Salt.}$$

So we have; $Y = X_1 + X_2 + X_3 + X_4$

The neuro – fuzzy model is given as

$$Y_d = \sum X_i W_i$$

where Y_d = desired output,

X_i = variable constituents,

W_i = attach weights.

The structure of neuro fuzzy model is presented in Figure 3 while the simplified form of the model is presented in Figure 4.
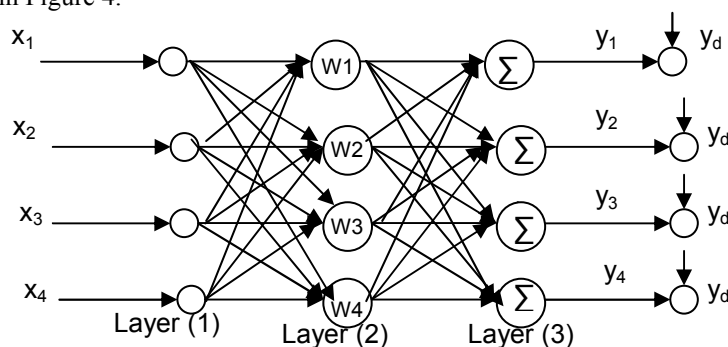

Figure 3: The structure of Neuro Fuzzy model.

The above structure is now modified to get the simplified structure of the neuro fuzzy model as presented below.
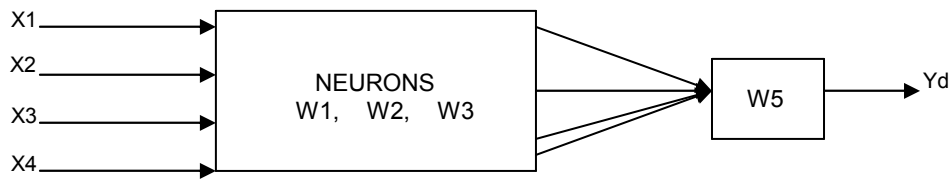

Figure 4: The simplified structure of Neuro Fuzzy model.

The input and output parameters for the neuro - fuzzy model with their identified variables are now presented in Table 3 below.

Table 3: Identified variables for Neuro - Fuzzy model input and output parameters.

Variable Name	Description	Fuzzy Variables.
A_bG_r	Abrasive Grains	Coarse, Medium, Fine, Very Fine.
S_iS_a	Silicon Sand	Coarse, Medium, Fine, Very Fine.
P_eC_o	Petroleum Coke	Coarse, Medium, Fine, Very Fine.
S_aD_u	Saw Dust,	Coarse, Medium, Fine, Very Fine.
$C_oS_{a.}$	Common Salt.	Coarse, Medium, Fine, Very Fine.

In the production of the abrasive grains or grits, it was observed that the fuzzy variables fine and very fine gave the same result as that of the fuzzy variable fine. Therefore, the neuro - fuzzy model with their identified variables are now reduced to the form presented in Table 4.

Table 4: Normalized identified variables for Neuro - Fuzzy model input and output parameters

Variable Name	Description	Fuzzy Variables.
A_bG_r	Abrasive Grains	Coarse, Medium, Fine.
S_iS_a	Silicon Sand	Coarse, Medium, Fine.
P_eC_o	Petroleum Coke	Coarse, Medium, Fine..
S_aD_u	Saw Dust,	Coarse, Medium, Fine.
$C_oS_{a.}$	Common Salt.	Coarse, Medium, Fine.

Therefore, the fuzzy model relates the desired output Y_d to the output Y.

Considering the output parameters from the neuro fuzzy model, we have;

    (1) $(Y_d - Y)$ = Negative (N) = Optimistic (O_p),

    (2) $(Y_d - Y)$ = Zero (Z) = Normal (N),

    (3) $(Y_d - Y)$ = Positive (P) = Pessimistic (P_e).

These parameters are to be processed to arrive at the specified desired output by using the following base rules:

    (1) IF $(Y_d - Y)$ = N AND $(Y_d - Y)$ = N continues, THEN output = Optimistic (O_p).

    (2) IF $(Y_d - Y)$ = Z AND $(Y_d - Y)$ = Z continues, THEN output = Normal (N).

    (3) IF $(Y_d - Y)$ = P AND $(Y_d - Y)$ = P continues, THEN output = Pessimistic(P_e)

For the effective production of silicon carbide grains, three major important parameters are considered. These are (1) silica sand (S_iS_a), petroleum coke (P_eC_o) and temperature (T_e). Denoting silica sand by S_i, petroleum coke by P_e and temperature by T_e, we now represent these input parameters by a neuro - fuzzy structure with a network as presented in Figure 5.
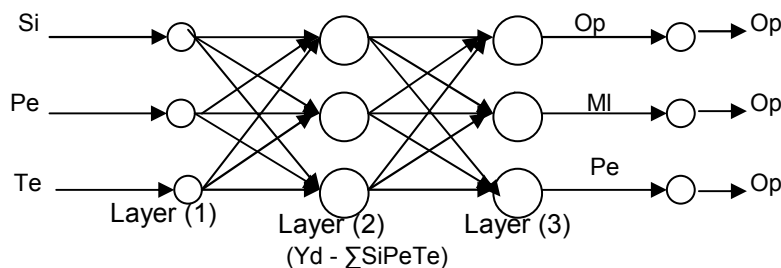

Figure 5: Neuro - Fuzzy input – output parameters.

were S_i, P_e, T_e are input parameters, O_p, M_l, P_e are output parameters, Y_d is the desired output and $(Y_d - \sum S_iP_eT_e)$ is the linguistic variable.

3.2 Neuro Fuzzy Output Parameters

The output parameters are;
(1) High grade grinding wheel (Optimistic, O_p),
(2) Normal grade grinding wheel (Most Likely, M_l),
(3) Poor grade grinding wheel (Pessimistic, P_e).
The Linguistic Variables;
(1) $(Y_d - \sum S_i P_e T_e)$ = Negative (N) = HGGW = Optimistic (O_p)
(2) $(Y_d - \sum S_i P_e T_e)$ = Zero (Z) = NGGW = Most Likely (M_l)
(3) $(Y_d - \sum S_i P_e T_e)$ = Positive (P) = PGGW = Pessimistic (P_e).
The neuro fuzzy model is now represented with a simplified fuzzy network as presented in Figure 6.
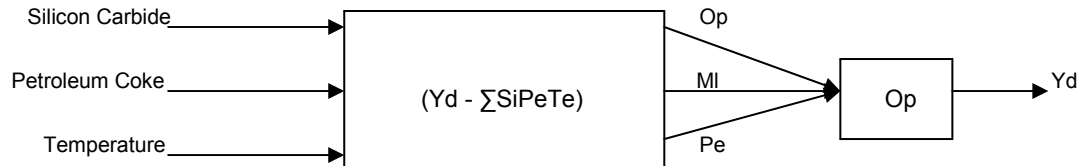

Figure 6: Simplified Neuro - Fuzzy network.

The components of fuzzy logic control model for the production of abrasive grains with membership functions are presented in Table 5.

Table 5: Relationship between Fuzzy output and membership function.

Level	Interpretation	Fuzzy Output	Linguistic Variables.
1	Optimistic	Negative	$(Y_d - \sum S_i P_e T_e)$
2	Most Likely	Zero	$(Y_d - \sum S_i P_e T_e)$
3	Pessimistic	Positive	$(Y_d - \sum S_i P_e T_e)$

The degree of relationship between fuzzy output and membership function ranges from 0 to 1.0 (Yu and Skibniewski).

4. The Grinding Wheel System Operating Rules

INPUT No 1: {"Input", Negative (O_p), Positive (P_e), Zero (M)}.
INPUT No. 2 {GN– Getting Negative (O_p), GP- Getting Positive (P_e), GZ- Getting Zero (N)}.
Where O_p is optimistic, P_e is pessimistic and M is most likely.
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 5 is now presented in Figure 7.
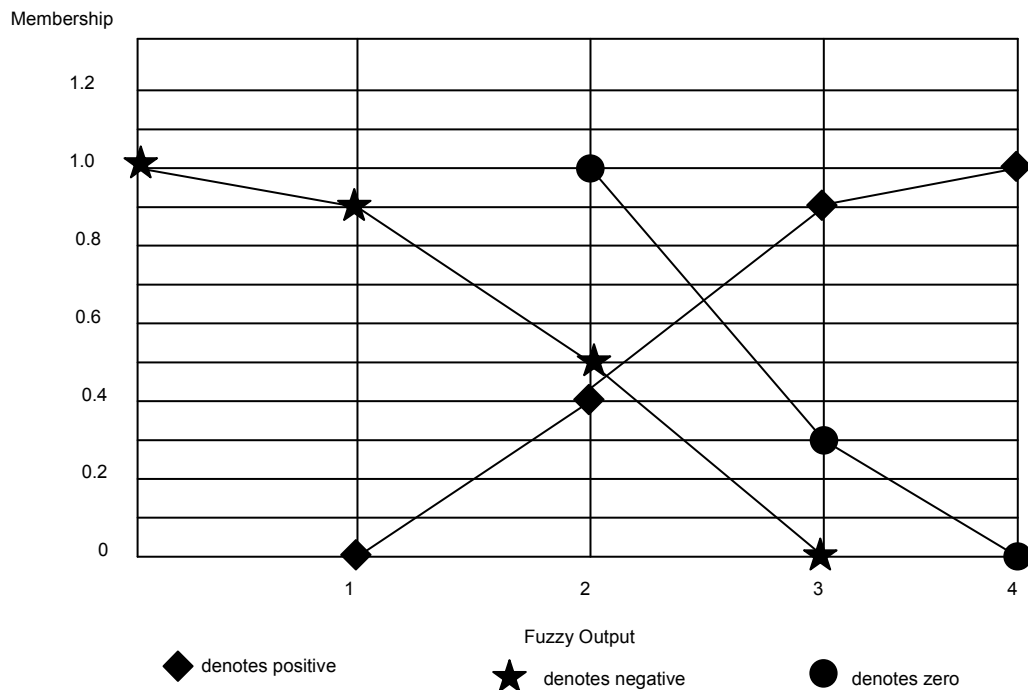
Figure 7: Graph of Fuzzy Logic control model

The interpretation of the graph shows that:

i. When the quality of the desired grinding wheel is lower than the quality of the grinding wheel obtained the model prompts negative (optimistic output).

ii When the quality of the desired grinding wheel is the same as the quality of the grinding wheel obtained model prompts zero (Most Likely output).

iii. When the quality of the desired grinding wheel is higher than the quality of the grinding wheel obtained the model prompts positive (pessimistic output).

5. Conclusion

A grinding wheel is one of the most versatile cutting tools used for removing material from machine parts by abrasion. It is an expendable wheel that carries an abrasive compound on its periphery. Grinding wheels are made of small, sharp and very hard natural or synthetic abrasive particles bonded together by a suitable bonding material. Neuro fuzzy models were used to analyze the contribution of each of the component elements of a typical grinding wheel made of silicon carbide abrasive material. The prominent constituents of a silicon carbide grinding wheel include; silica sand, petroleum coke, saw dust and sodium chloride. Silicon carbide and petroleum coke are the most important constituents. It was discovered that the size of the grains and its spacing, volumetric proportion of grains, volumetric proportion of bonding material and volumetric proportion of pores influence greatly the performance characteristics of a grinding wheel.

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