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Neuro - Fuzzy Analysis for Silicon Carbide Abrasive Grains Production.

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Abstract

Grinding wheels are made of very small, sharp and hard abrasive materials or grits held together by strong porous bond. Abrasive materials are materials of extreme hardness that are used to shape other materials by a grinding or abrading action and they are used either as loose grains, as grinding wheels, or as coatings on cloth or paper. The manufacture of abrasives in Nigeria has been severely impeded by the difficulty of identifying suitable local raw materials and the associated local formulation for abrasives with global quality standards. This paper presents a study on application of neuro fuzzy to the formulation of silicon carbide abrasives using locally sourced raw materials in Nigeria. Five local raw material substitutes were identified through pilot study and the fuzzy variables of the raw materials were identified while the input parameters, output parameters, the linguistic variable and the desired output were used to get the true result.

Key words: Abrasive Materials, Local raw material, Silicon carbide abrasives, Pilot study, Neuro Fuzzy.

1.0 Introduction

Abrasive materials are very hard mineral materials used to shape, finish, or polish other materials. The abrasive materials are processed in a furnace after which they can further be pulverized and sifted into different grain sizes called grits, ([10] and [11]). Abrasive materials for grinding, honing, lapping, and super finishing are classified into two groups, natural and synthetic abrasive materials and except for diamonds, manufactured abrasives have almost totally replaced natural abrasive materials. The most important physical properties of abrasive materials are; hardness, brittleness, toughness, grain shape and grain size, character of fracture, purity and uniformity of the grains [14].

Natural abrasive materials are those materials that are found existing naturally and are used for the manufacture of abrasive grains 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 ([5], [6], [7] and [13]). Corundum and emery have long been used for grinding purposes and both are made up of crystalline aluminium oxide in combination with iron oxide and other impurities. Like sand stone, these materials lack a uniform bond and are not suitable for high- speed grinding work. Diamond wheels, made with resinoid bond, are especially useful in sharpening cemented-carbide tools. In spite of high initial cost, they have proved to be economical because of their rapid cutting ability, slow wear, and free cutting action, [1].

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 [16]. 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 [16]. 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 [12] and [18]. 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, [21]. 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.

Silicon carbide abrasive is manufactured in an Acheson graphite electric resistance furnace charged with a mixture of approximately 60 percent silica sand and 40 percent finely ground petroleum coke. A small amount of saw dust is added to the mix to increase its porosity so that the carbon monoxide gas formed during the process can escape freely. Common salt is also added to the mix to promote the carbon-silicon reaction and to remove impurities in the sand and coke. The mixture is heated in an Acheson graphite electric resistance furnace to temperature of about 1800^oC to 2200^oC, at which point a large portion of the load crystallizes to form silicon carbide abrasives [8]. Silicon carbide which is formed in the Acheson furnace varies in purity, according to its distance from the graphite resistor heat source. Colorless, pale yellow and green crystals have the highest purity and are found closest to the resistor. The color changes to blue and black at greater distance from the resistor, and these darker crystals are less pure [2].

Abrasives for grinding wheels may be acquired in Nigeria either through importation or by manufacturing. Acquiring abrasives in Nigeria through importation may be hindered due to lack of foreign currency and this may not be profitable. Therefore, the feasible alternative for acquiring abrasives for grinding wheels in Nigeria is to manufacture them locally and in this case, foreign firms may have to establish in Nigeria but the literature is sparse on such establishment. Therefore, Nigerians need to manufacture their abrasives directly and to do this; Nigerians need to go abroad for training to acquire the relevant skills. However, from experience, such individuals are handicap because using local raw materials with foreign formulations could not yield abrasives of international standard. Therefore, the need for local manufacture of abrasives for grinding wheels for our various industries using locally sourced raw materials with local formulations is the aim of this research work.

Fuzzy set theory provides a remedy for any lack of uncertainty in the data, [9] 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 [15]. 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 [17]. 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 [4]. 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, [3]. 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 [20], computational neural networks offer exciting advantages, such as learning, adaptation, fault-tolerance, parallelism and generalization [19]. 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 Materials And Method

The various component materials used for the production of ISO certified silicon carbide abrasives include: silica sand, petroleum coke, sawdust and sodium chloride, [8]. Some of these raw materials are either not available locally in Nigeria or are very unstable. Attention was therefore focused at discovering local substitutes for these raw materials for use in the formulation and manufacturing of silicon carbide abrasives. Therefore, a pilot study was therefore conducted on various raw materials to identify suitable local material substitutes and quartz, coal, sodium carbonate, sawdust and sodium chloride were suitable substitutes.

The abrasive grains were formulated and manufactured using varying proportions of locally sourced raw materials. Quartz (Qa), coal (C_o), sodium carbonate (S_oC_a), sawdust (S_a) and sodium chloride (S_oC_h). These components were properly mixed for the production. We now develop neuro – fuzzy model for the production of silicon carbide abrasive grains as follows:

$A_bG_r = Q_a + C_o + S_oC_a + S_a + S_oC_h$

These parameters are now denoted as follows.

$Y = A_bG_r =$ Abrasive Grains, $X_1 = Q_a =$ Quatz, $X_2 = C_o =$ Coal, $X_3 = S_oC_a =$ Sodium Carbonate

$X_4 = S_a =$ Sawdust, $X_5 = S_oC_{h.} =$ Sodium Chloride.

So we have; $Y = X_1 + X_2 + X_3 + X_4 + X_5$.

The neuro – fuzzy model is given as $Y_d = \sum X_iW_i$.

were Y_d = desired output, X_i = variable proportion of constituents, W_i = attach weights.

The structure of neuro fuzzy model is presented in Figure 1, and it is is made of three distinct parts namely input, layers, and output. The inputs are denoted by ‘X’. This could be X1, X2 and X3 for the framework shown in Figure 1.

Each of these ‘X’ values may represent different inputs such as quartz, coal, sodium carbonate, sawdust, sodium chloride, temperature, etc. As such, the number of ‘X’ values may be equivalent to the number of input parameters that we are considering. In this case, the structure of the diagram would be more complicated than what is illustrated above. The second division of the neurofuzzy structure consists of layers which are interconnections between the input and output neurons. In this particular defined instance, three layers are specified and they are layers 0, 1, and 2. The next segmentation of the neurofuzzy structure is the output. This is represented by ‘y’. Particularly, we have y1, y2, and y3. The output has to be refined in order to obtain the desired output. The refined output is referred to as the desired output, ‘yd’. For a clearer view of the neurofuzzy model, the simplified schematic layout diagram in Figure 2 is employed.

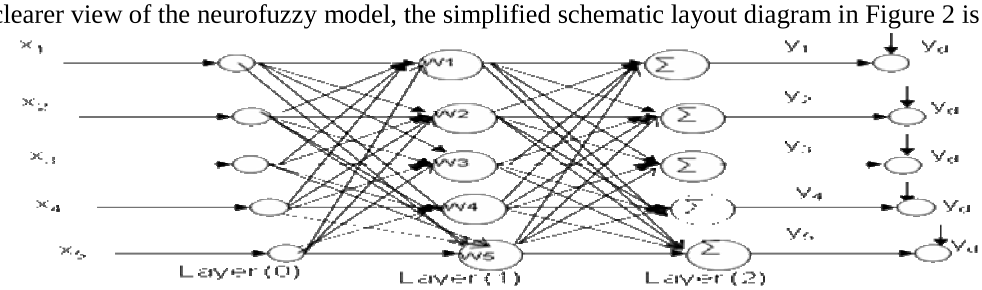

Fig.1: The Structure of Neuro Fuzzy Model.

The above structure is now simplified for a clearer view and better understanding of the neurofuzzy model structure above.

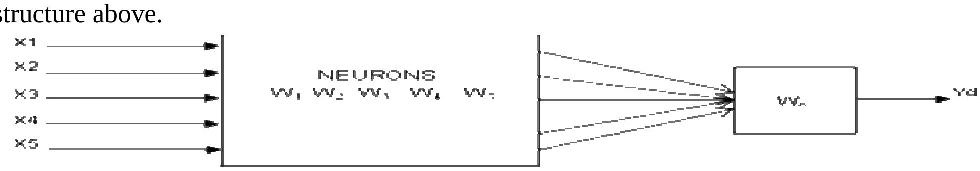

Fig. 2: Simplified Neuro Fuzzy Model.

The input and output parameters for the neuro - fuzzy model with their identified variables are now presented in Table 1 below.

$X_1 = Q_a =$ Quatz, $X_2 = C_o =$ Coal, $X_3 = S_oC_a$ = Sodium Carbonate

$X_4 = S_a =$ Sawdust, $X_5 = S_oC_{h.}$ = Sodium Chloride.

Table 1: 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.
Q_a	Quartz	Coarse, Medium, Fine, Very Fine.
C_o	Coal	Coarse, Medium, Fine, Very Fine.
S_oC_a	Sodium Carbonate	Coarse, Medium, Fine, Very Fine.
S_a	Sawdust,	Coarse, Medium, Fine, Very Fine.
$S_oC_{h.}$	Sodium chloride	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 2..

Table 2: Normalized Identified Variables for Neuro - Fuzzy Model Input and Output Parameters.

Variable Name	Description	Fuzzy Variables.
A_bG_r	Abrasive Grains	Coarse, Medium, Fine.
Q_a	Silicon Carbide	Coarse, Medium, Fine.
C_o	Petroleum Coke	Coarse, Medium, Fine..
S_oC_a	Sodium Carbonate	Coarse, Medium, Fine,
S_aD_u	Saw Dust,	Coarse, Medium, Fine.
$S_oC_{h.}$	Sodium chloride	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) $(Y_d – Y)$ = Positive (P) = Optimistic (O_p),

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

(3) $(Y_d – Y)$ = Negative (N) = Pessimistic (P_e).

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

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

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

(3) IF $(Y_d – Y)$ = N AND $(Y_d – Y)$ = N continues, THEN output = Pessimistic(P_e)

For the effective production of silicon carbide grains, three major important parameters were considered. These are: the core material (quartz), the reactant (coal) and melting temperature since sodium carbonate, sawdust and sodium chloride are catalysts in the formulation. Denoting quartz by Q_a, coal by C_o and temperature by T_e, we now represent these input parameters by a neuro fuzzy network as follows:

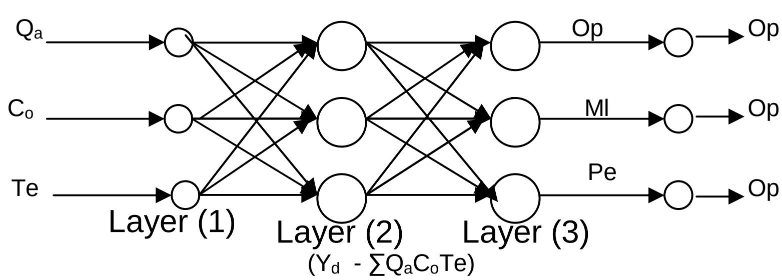

Fig. 3: Neuro Fuzzy Input – Output Parameters.

Were Q_a, C_o, T_e are input parameters, O_p, M_l, P_e are output parameters, Y_d is the desired output and $(Y_d - \sum Q_aC_oT_e)$ is the linguistic variable.

Output Parameters.

The output parameters are;

(1) High grade silicon carbide abrasives (Optimistic,O_p), (2) Normal grade silicon carbide abrasives (Most Likely, M_l),

(3)Normal grade silicon carbide abrasives (Most Likely, M_l),(4) Poor grade silicon carbide abrasives (Pessimistic, P_e).

Poor grade silicon carbide abrasives (Pessimistic, P_e).

The Linguistic Variables;

(1) $(Y_d - \sum S_i P_e T_e)$ = Positive (P) = HGSCA = Optimistic (O_p)
(2) $(Y_d - \sum S_i P_e T_e)$ = Zero (Z) = NGSCA = Most Likely (M_l)
(3) $(Y_d - \sum S_i P_e T_e)$ = Negative (N) = PGSCA = Pessimistic (P_e).

The neuro fuzzy model is now represented with a simplified fuzzy network.

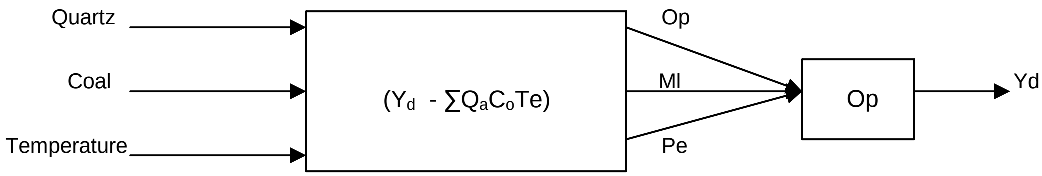

Fig.4: Neuro Fuzzy Network.

The components of fuzzy logic control model for the production of abrasive grains with membership functions are presented in Table 3.

Table 3: Relationship Between Fuzzy Output and Membership Function.

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

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

The membership function for the abrasive grain size is given in Figure 5.

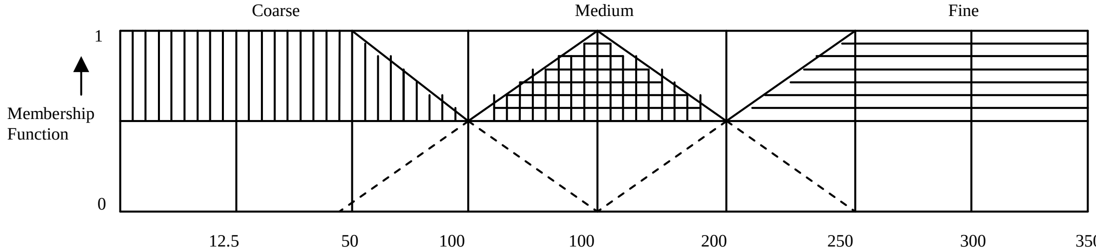

Fig. 5: Membership Function for Grain Size.

The Components of Fuzzy Logic Model.

The components of the fuzzy logic control of the abrsive grains production can now be represented with membership functions as presented in Table 4.

Table 4: Components of Fuzzy Logic Model.

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

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

(1) IF $(Y_d - \sum S_i P_e T_e)$ = P AND $(Y_d - \sum S_i P_e T_e)$ = VHP continues, THEN output O_p. (2) IF $(Y_d - \sum S_i P_e T_e)$ = Z AND $(Y_d - \sum S_i P_e T_e)$ = VHZ continues, THEN output Nil

(3) IF $(Y_d - \sum S_i P_e T_e)$ = N AND $(Y_d - \sum S_i P_e T_e)$ = VLN continues, THEN output Nil.

The 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 graphical illustration of Table 4 is presented in Figure 6 and it explains the nature and behavior of the various grades of the produced silicon carbide abrasive grains.

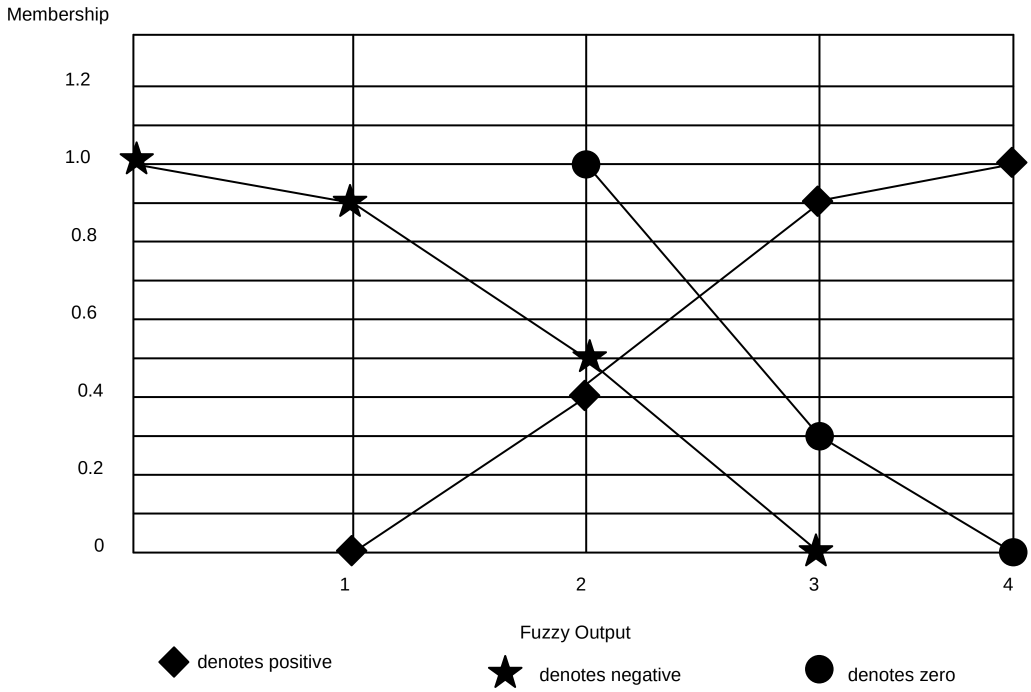

Figure 6: Graph of Fuzzy Logic Control Model

The interpretation of the graph shows that:
i. When the grade of silicon carbide abrasives produced is higher than the desired grade of the abrasives the model prompts positive (optimistic output).
ii. When the grade of silicon carbide abrasives produced is lower than the desired grade of the abrasives the model prompts negative (pessimistic output); and
iii. When the grade of silicon carbide abrasives produced is the same as that of the desired grade of the abrasives the model prompts zero (Most Likely output).

Conclusion

The formulation and manufacture of silicon carbide abrasives involves various factors such as temperature, melting time, pressure etc. Five local raw material substitutes for the formulation and manufacture of silicon carbide
abrasives were identified from pilot study and they include: quartz, coal, sodium carbonate, sawdust and sodium chloride. Neuro fuzzy network and models were used to carefully analyse and control the silicon carbide abrasives formulation process so as to get the desired output with acceptable quality of silicon carbide abrasive grains for grinding wheel manufacture. We have developed a neurofuzzy approach in the formulation and manufacture of silicon carbide abrasives for grinding wheels. This is a new contribution to the body of knowledge on the use of neuro-fuzzy logic in design and analysis of processes as was earlier used by others in road bump design.

References.

[1] Arunachalam, N. and Ramamoorthy, B. (2007). Texture Analysis for Grinding Wheel Wear Assessment Using Machine Vision. *Journal of Engineering Manufacture*. 221(3): 419-430.
[2] Bakken, J.A., Jensen, R., Monsen, B., Raaness, O., and Wærnes, A.N., (1998). Thermal Plasma Process Development in Norway. *Journal of Pure and Applied Chemistry*, IUPAC. 6(3): 23- 30.
[3] Barai, S.V and Nair, R.S., (2004). "Neuro-Fuzzy Models for Constructability Analysis" ITcon 9: 65 – 73.
[4] Benachaiba, C., Dib, S. and Abdelkhlek, O. (2006). "Genetic Algorithm-Based Self-Learning Fuzzy PI Controller for Shunt Active Filter" International Journal of Applied Engineering Research 1 (2): pp. 203-216.
[5] Brecker, J.N., (2006). Analysis of Bond Formation in Vitrified Abrasive Wheels.*Journal of the American Ceramic Society*. 57(11): 486 – 489.
[6] Clark A. C., Shih A. J., Hardin C.W., Lemaster, R.L. and McSpadden S. B. (2003). Fixed Abrasive Diamond Wire Machining, Part1. Process Monitoring and Wire Geometry and Tension. *International Journal of Machine Tools and Manufacture*, 43(27): 523-532.
[7] Eckart U., Frank, S. and Christoph, H. (2007). Economical Aspects of Profiling Diamond-Grinding Wheels. *International Journal of Manufacturing Technology and Management.* 12(1/2/3): 93 - 107.
[8] Elston, E. D. (2006); Ceramic Abstracts. *Journal of the American Ceramic Society*. 3(6): 501- 520.
[9] Jagannath, R., Naresh, N. G and Pandey, K. M., (2007). "Studies on Pressure Loss in Sudden Expansion in Flow through Nozzles: A Fuzzy Logic Approach" ARPN Journal of Engineering and Applied Sciences; 2 (2): 50-61.
[10] Maksoud, T. M. and Atia, M. R., (2004). Review of Intelligent Grinding and Dressing Operations" *Journal of Machining Science and Technology*. 8: 263-276.

[11] Odior, A. O. and Oyawale, F. A., (2008a). Application of Neuro Fuzzy to Component Elements of a Grinding Wheel." *Global Journal of Engineering and Technology*, 1: 329-335.
[12] Odior, A.O. and Oyawale, F.A., (2008b)."A Neuro – Fuzzy Approach to Grinding Process Control" Global Journal of Engineering and Technology. 1 (2): 153 – 159.
[13] Odior, A.O., (2002). "Development of a Grinding Wheel from Locally Available Materials". The Journal of Nigerian Institution of Production Engineers. 7(2): 62 - 68.
[14] Onibonoje, O.I. and Oyawale, F.A. (1998). Manufacture of Abrasive Paper from Local Raw Materials. Proceedings of the Nigerian Institute of Industrial Engineers, Ibadan.
[15] Osofisan, P.B. and Afunlehin, O. A., (2007), "Application of Neural Network to Improve Dynamic Branch Prediction of Superscalar Microprocessors" Pacific Journal of Science and Technology. 8(1): 80-97.
[16] Scott, G., (2010). Sandpaper: BeautifulWood.Net web site. Retrieved 27 May, 2010 from http://www.beautifulwood.net/html/sandpaper.html.
[17] Siwaporn, K., (2007). "Optimal Sample Size Selection for Torusity Estimation Using a PSO Based Neural Network" Thammasat International Journal of Science and Technology. 12(2): 64 – 77
[18] Suryarghya, C. and Paul, S. (2007). Numerical Modeling of Surface Topography in Superabrasive Grinding. *The International Journal of Advanced Manufacturing Technology*. 13(6): 45–57.
[19] Wasserman, P. D., (1989). Neural Computing, Van nostrand Reinhold, New York.
[20] Zadeh, L. A., 1988. "Fuzzy logic", IEEE Computer,1988, April, 83-92.
[21] Zhong, Z.W. and Venkatesh, V.C. (2008). Recent Developments in Grinding of Advanced Materials. *The International Journal of Advanced Manufacturing Technology*. 6(3): 35 – 44.