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Mathematical Modeling using Artificial Neural Networks for Quality Evaluation in the Machining of Fe-Al Alloy with PCBN Tools

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***Abstract*— Machining experiments are conducted on Fe-Al alloy with PCBN inserts of different tool geometry. The corresponding roughness values of the machined surface are measured. Mathematical model is developed using artificial neural networks to study the influence of tool geometry on the surface roughness. The equation thus formulated evaluates the machining performance. It would be useful in the selection of suitable tool geometry to improve the machining quality. The analytical and experimental values of surface roughness are found to be in good order that confirms the fitness of the model. It would be useful in evaluation of the machining quality.**

***Index Terms*— Mathematical Modeling, Artificial Neural Networks, Fe-Al Alloy, PCBN Inserts, Tool Geometry, Surface Roughness**

I. INTRODUCTION

Aluminium-Steel (Fe-Al) mechanical alloy offers excellent strength-weight ratio and toughness. They are important in critical applications and in complex situations. The Fe-Al alloy possesses other favorable attributes like superior resistance to corrosion, wear and thermal distortions [1]. These features make the alloy more suitable in applications like automobile, aerospace, marine, defence, bulk containers and food processing equipments. On the other hand, the alloy suffers from poor machinability, because of which the cutting tool rapidly blunts and results in poor surface finish [2]. This tendency hampers the machining quality, economy and productivity. Owing to this machining difficulty, the alloy slips preferential treatment, what it deserves.

Cutting tool geometry plays a vital role in machining quality, which clearly appears in the form of roughness on the machined surface [3]. The selection of the nose radius (R), cutting angle (γ) and rake angle (α) is based upon the tool and work-piece materials, type of operation and required metal-removal-rate. Bigger nose radius erases the feed marks and improves the surface finish but it is limited by chatter that spoils the quality. Cutting angle provides proper tool action. Rake angle facilitates smooth chip-flow and ease shear of metal, but weakens the tool-strength. Hence, careful consideration of these geometrical parameters becomes important in machining of the components [4].

Machining experiments involving turning operation are performed on Fe-Al alloy specimens with PCBN tool inserts. The tool geometrical parameters are successively varied and corresponding surface roughness values are measured.

In normal practice, suitable tool geometry is selected from cutting tool handbooks, but no such data is available for this emerging metal. Trial & error method does not yield satisfactory results. Each parameter of tool geometry is required to be selected from a wide range, necessitating large number of tools and experiments. Mathematical modeling using artificial neural networks (ANN) approach is adopted in the current work to simplify the process of tool geometry selection with a fewer number of tools, lesser time and cost.

ANN is a versatile and a smart approach preferred by researchers and analysts in diversified applications. It can handle a wide range of linear and non-linear data without requiring implicit assumptions [5]. Mathematical equation is framed with experimental data to relate surface roughness with tool geometry. The fitness of the equation is evaluated. The equation facilitates prediction of the surface roughness for the given tool geometry. It would be useful in the selection of proper tool geometry to machine the Fe-Al alloy components with PCBN inserts. It would also enhance the machining prospects.

II. METHODOLOGY

Fe-Al specimens are pre-machined to the size. Machining experiments are conducted on the specimens using PCBN tool inserts. Tool geometry is varied and corresponding surface roughness is measured. Mathematical model is developed using ANN technique. Equation is formulated for surface roughness as a function of tool geometry.

III. EXPERIMENTATION

A. *Fe-Al Alloy Specimen Preparation*

Fine particles of pure Aluminium and Steel are milled in the planetary ball mill at suitable speed for considerable time. Proportions of the elements are adjusted according to the requirement. Small addition of ethanol controls the process characteristics. The presence of Argon protects the mixture from oxidation. The powdered mixture is then compacted to the required shape and size using press tools, followed by annealing in vacuum furnace. The microstructure is examined to assess the structural integrity and other metallurgical characteristics as shown in Fig. 1.The porous structure and brittle inter-metallic molecular bonding are observed, which would be causing poor machinability.

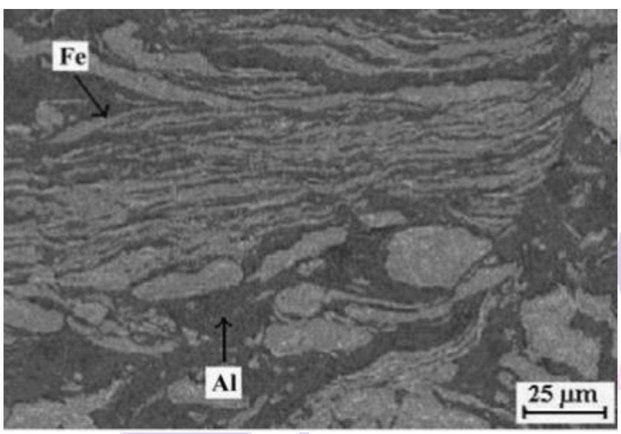

Fig. 1.Microstructure of Fe-Al Mechanical Alloy captured by Scanning Electron Microscope

Mechanical properties of the alloy are illustrated in Table 1. Superior strength-weight ratio, higher stiffness and wear resistance are observed.

TABLE I
MECHANICAL PROPERTIES OF FE-AL ALLOY

Relative Density (%)	Flexural Strength (MPa)	Strain at Breaking point (%)	Micro Hardness (HV100g)
95.00	831.30	3.20	700

B. *Machining Experiments*

Specimens are pre-machined to required size. Praga CNC lathe machine is employed to perform turning operations under flooded cooling condition. The specimen is attached to power chuck through mandrel. PCBN tool inserts with tool holders are fixed in tool turret. CNC part program with parametric values of speed, feed and depth of cut as illustrated in Table 2 is executed for multiple passes. Constant cutting speed option is selected in the part program to vary the rotational speed (rpm) according the diminishing diameter. All the experiments are performed at constant speed, feed and depth of cut. Experiments are conducted with three levels of tool geometry parameters as shown in Table 3. The machined specimens are inspected for surface roughness using Mitutoyo Taly-surf.

TABLE II
CUTTING PARAMETERS

Cutting Speed V (m/min)	Feed Rate f (mm/rev)	Depth of Cut d (mm)
150	0.030	0.5

TABLE III
TOOL GEOMETRY PARAMETERS

Parameter \ Level	1	2	3
Nose Radius R (mm)	0.4	0.8	1.2
Cutting Angle γ (degrees)	30	60	90
Rake Angle α (degrees)	-2	-5	-8

C. *Artificial Neural Networks*

The paper presents ANN approach to model the machining performance on Fe-Al alloy with PCBN tool inserts. It is a collection of connected units called artificial neurons. The processing ability of the network is stored in the connection strengths of the inter-units called weights. They are adjusted during training process of the network to minimize error i.e. the difference between analytical and actual outputs. The mean squared error (MSE) function is used to assess these errors. ANNs are of two types based upon the architecture viz. feed-forward and feed-backward networks. The first one allows the input signals to output. It is suitable to frame equations relating a set of input variables with one or more outputs.

Multi-layers perceptron (MLP) is an extensively used feed-forward network. A typical MLP network comprises of input, hidden and output layers as shown in Fig 2. Input layer transfers the values of input variables to the hidden layer.

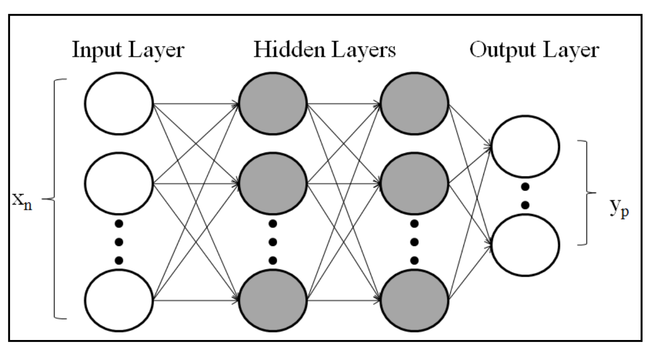

Fig. 2. Multi-layers Perceptron Network

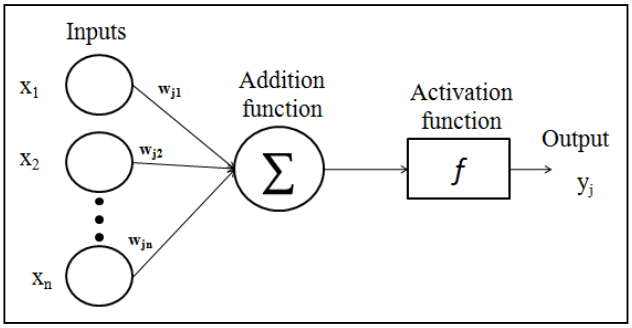

Fig. 3.Structure of an artificial neuron

The artificial neuron j performs addition function and activation functions as shown in Fig. 3. The addition function (1) sums up the inputs after assigning the weights w_{ji} from the input layer. The activation function 'f' activates the functional value with a bias b_j as shown in (2). In the present case, sigmoid function is selected as described by (3).

$$S_j = \sum_{i=1}^{n} w_{ji} x_i \tag{1}$$

$$y_j = f\left(\sum_{i=1}^{n} w_{ji x_i} + b_j\right) \tag{2}$$

$$f_j(x) = \frac{1}{1 + \exp(-S_j + b_j)} \tag{3}$$

Back propagation algorithm is used to train MLP network to adjust the weights and minimize the errors. In the current work, Levenberg-Marquardt back propagation algorithm is used. The training process is carried out in two stages viz. forward stage and backward stage. In the forward stage, the weights are assigned and the input values are propagating through the network layers to the output and the error is calculated. In backward stage, the error is propagated back through the layers to re-adjust the weights in order to minimize the error.

IV. Results and Discussion

The values of input (R, γ, α) and output (Ra) parameters are normalized between 0.1 and 0.9. The normalized values are imported in Neural Network Toolbox available in Matlab-R2011a. The proposed architecture of the network is illustrated in Fig 4. The number of neurons in the hidden layer 'j' is selected as twice the number of neurons in input layer as per the recommendations [6]. The training parameters are assigned as follows. The proportion of imported data for training, validation and testing is taken as 70%, 15% and 15% respectively. The goal of the MSE is set as 10^{-4}, number of epochs to 1000 and validation checks as 100.

The training results are as follows. The performance of the network is successful at epoch 7 with MSE=0.0427 % as shown in Fig 5. This shows the minimal error between the analytical and experimental outcomes, which is a good sign.

The regression plots for target data versus ANN outputs are shown in Fig 6. The coefficient of determination 'R' is about 99% for training, validation, testing and overall data. It shows a good control on the reliability of the network.

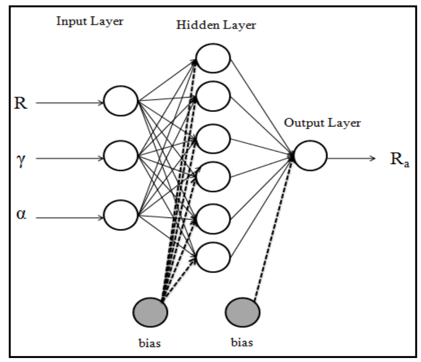

Fig. 4.Proposed Architecture of the Neural Network

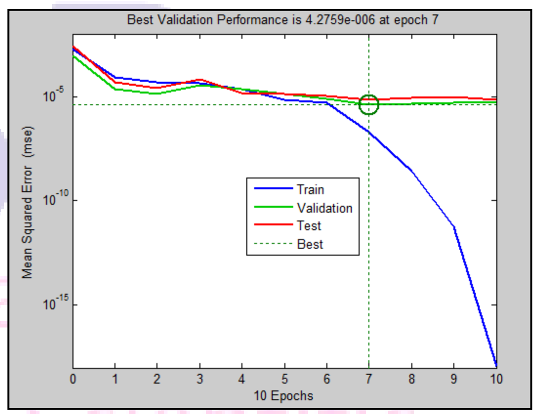

Fig. 5.MSE performance plot of the ANN

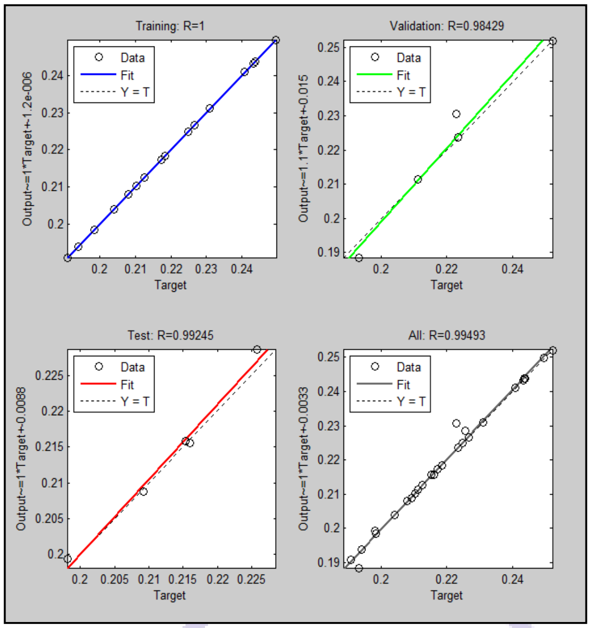

Fig. 6.Regression Plots for experimental values versus ANN outputs

The mathematical equation generated between the input and output variable by the ANN is illustrated in (4). The activation functions f_j (j=1, 2...6) are calculated as shown in (5). The weights w_{j1}, w_{j2} and w_{j3} and biases b_j are enlisted in Table 4.

$$R_a = -4.0123 f_1 - 2.7470 f_2 + 1.8112 f_3 - 1.5231 f_4 + 3.9959 f_5 - 4.0051 f_6 + 1.6893 \quad - (4)$$

$$f_j = \frac{1}{1+\exp\left(-\left(w_{j1}R + w_{j2}\gamma + w_{j3}\alpha + b_j\right)\right)} \quad - (5)$$

TABLE IV
WEIGHTS AND BIASES BETWEEN INPUT AND HIDDEN LAYERS

Neuron j	w_{j1}	w_{j2}	w_{j3}	b_j
1	2.1873	4.3656	0.90735	-4.0123
2	5.7384	0.8669	-0.49901	-2.747
3	-2.3129	-0.92677	1.9625	1.8112
4	-2.7849	-1.4668	- 3.7763	-1.5231
5	2.3502	3.7322	-0.03293	3.9559
6	-3.3158	0.30893	4.5217	-4.0051

The ANN outputs are de-normalized to obtain the predicted surface roughness values. Figure 7 shows a comparison between the experimental and predicted surface roughness values. The experimental and predicted surface roughness values in all the experiments are in good agreement that confirms the fitness of the mathematical model.

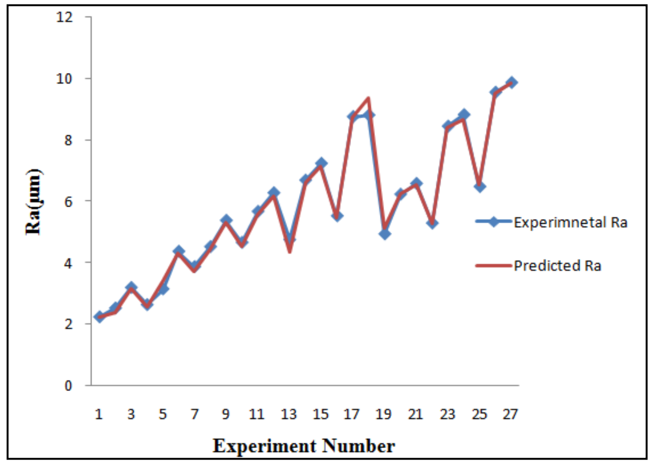

Fig. 7.Comparison of experimental and analytical surface roughness values

V. CONCLUSION

Machining experiments and subsequent mathematical modeling shows that surface roughness is very sensitive to tool geometry. Proper selection of tool geometry ensures better machining quality. Mathematical modeling using ANN approach is well suited in machining of Fe-Al alloy using PCBN tool inserts. The work has simplified the tool geometry selection from a wide range by using fewer tools and lesser number of experiments. Hence, this method is cost effective and takes shorter manufacturing lead times.

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REFERENCES

[1] SONG Haixia, WU Yunxin, TANG Chuan'an, YUAN Shuai, GONG Qianming and LIANG Ji.. "Microstructure and Mechanical Properties of Fe-Al Intermetallics Prepared by Mechanical Alloying and Hot-Pressing," *Tsinghua Science and Technology*. vol. 14, no. 3, pp.300-306. June. 2009.

[2] D. Srinivas Rao, A. Krishnaiah, Y. Krishna and Syed Adil. "Sustainable Machining of Fe-Al Mechanical Alloy using PCBN Tool inserts," *International Journal of Engineering Research in Mechanical and Civil Engineering*. vol. 2, no. 3, pp. 499-504, March. 2017.

[3] Dilbag Singh and P. Venkateswara Rao. "Optimization of Tool Geometry and Cutting Parameters for Hard Turning," *Materials and Manufacturing Processes*. vol. 22 no.1, pp. 15-21, March. 2007.

[4] David A. Stephenson and John S. Agapiou. "Metal Cutting Theory and Practice," Third Edition. CRC Press. 2016

[5] Samya Dahbi, Latifa Ezzine and Haj E.L. Moussami. "Modeling of Cutting Performances in Turning Process using Artificial Neural

Networks," *International Journal of Engineering Business Management*. vol. 9, pp. 1-13. June. 2017.

[6] Zhang G, Patuwo BE, and Hu M.Y. "Forecasting with artificial neural networks: the state of the art," *International Journal of Forecasting*. Issue. 14, pp. 35–62. 1998.