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Modeling of Machining Performance on Fe-Al Alloy using Artificial Neural Networks

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ABSTRACT

Machining experiments involving turning process are conducted on Fe-Al alloy specimens. Carbide inserts of different tool geometry are used. Roughness of the machined surface is measured, which represents the process quality. Mathematical model using artificial neural networks is developed with experimental data. Equation is formulated to relate surface roughness with tool geometry. Analytical and experimental results of surface roughness are found to be in good agreement. The model would be useful in the selection of optimum tool geometry for machining of Fe-Al alloy components with better quality.

KEYWORDS: Mathematical Modeling, Fe-Al Alloy, Tool Geometry, Surface Roughness, Artificial Neural Networks

INTRODUCTION

Fe-Al alloy is prepared in mechanical alloying process. It offers excellent strength-weight ratio and stiffness, which are very essential in critical applications. Superior resistance to corrosion, wear and thermal distortion are the favorable attributes of the alloy [1]. The metal is seriously considered in deserving applications like automobile, aerospace, defence, bulk containers and food processing equipments. But its poor response towards machining process causes rapid tool blunting and produces improper surface finish [2]. This factor limits the large scale application of the metal in the component form.

Cutting tool geometry exhibits significant influence on the machining performance. Properly selected tool geometry produces good surface quality and offers long service [3]. The surface roughness generated on the machined specimen reflects the tool performance.

Turning experiments are performed on the Fe-Al alloy specimens using CNC lathe machine with Coated Carbide tool inserts. The tool geometrical parameters viz. nose radius (R), cutting angle (γ) and rake angle (α) are varied and corresponding surface roughness (R_a) is measured. Larger nose radius erases the feed marks and improves the surface finish, but it is restricted by chatter that spoils the machined surface. Rake angle facilitates smooth chip flow and shearing of the metal, but it weakens the cutting edge. Cutting angle provides proper chiseling action. Hence, the proper selection of the tool geometry becomes very important in the machining process [4].

Tool geometry plays a vital role in the success of the machining process. It depends upon the tool and work-materials, type of operation and machining rate. As a normal practice, suitable tool-geometry is selected from the tool-manufacturers' catalog. Since the subject metal is not commercially available, no such data is available in standard handbooks. Thumb rule practice of tool-geometry selection does not yield good results. Hence, scientific evaluation of tool geometry is required to achieve better performance out of the cutting tool.

Each individual parameter of tool geometry varies in a wide range and a large number of tools are required. The experimentation time and cost goes beyond the reach. In order to simplify the task of selecting the optimum tool geometry from a wide range, with limited number of experiments and less time, mathematical modeling is adapted.

Mathematical modeling using artificial neural networks (ANN) technique is developed. ANN model is preferred by analysts and researchers due to its smart ability to handle linear and non-linear data in diversified systems without making any implicit assumptions unlike in other conventional modeling approaches [5]. Equation is formulated to correlate surface roughness with tool geometry. Mean Square Error – Performance plot and Regression plots are generated that show the reliability of the equation. The study of these plots reveals that anticipated values given by the equation are closer to actual measured values. It confirms the reliability of the equation and genuineness of the process. The model would be used to select the optimum tool geometry for better machining quality and improved tool-service.

EXPERIMENTATION

Fe-Al SPECIMEN PREPARATION

Specimens are prepared in solid-state diffusion process called mechanical alloying. Fine powders of Aluminium and Steel in equal proportion are milled in the planetary ball mill at about 300 rpm for approximately 3 hours duration. Ethanol is added in small proportion as process control agent. The ball milling process is carried out in the presence of Argon that protects the mixture from oxidation. The powders are compacted to sleeve form and annealed at 1100 ^{0}C in a vacuum furnace. The annealed specimens are polished and etched in Nital solution to remove any surface contamination. The microstructure of the specimen is examined under Scanning Electron Microscope to assess the structural integrity and other characteristics as shown in Fig 1.

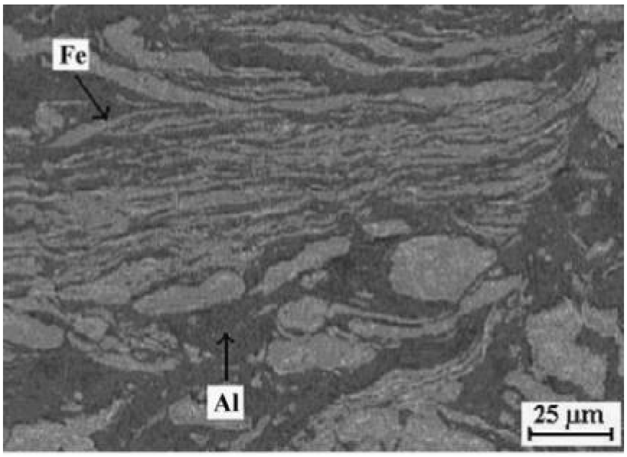

Fig1: Microstructure of Fe-Al Mechanical Alloy captured by Scanning Electron Microscope

Mechanical properties of the alloy are enlisted in Table 1. These values express superior strength-weight ratio, higher stiffness and wear resistance. The porous structure and brittle inter-metallic molecular bonding are observed in the structure, which causes machining difficulties.

Table 1. 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

MACHINING EXPERIMENTS

Specimens are pre-machined to required sizes in conventional process. Praga CNC Turn Station equipped with Siemens Control System is employed to perform turning operations under flooded cooling condition. Fixture is used to clamp the specimen in the power chuck. Carbide tool inserts of different geometry as illustrated in Table 2 with tool holders are fixed in the tool turret. CNC part program with parametric values of speed, feed and depth of cut as illustrated in Table 3 is executed for multiple passes. Constant cutting speed option is selected in the part program as rotational speed (rpm) has to be adjusted with decrease in diameter of the work-piece. Total of 27 experiments with different combination of tool geometry parameters are conducted. The machined specimens are inspected for surface roughness using Mitutoyo Taly-surf.

Table 2. 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

Table 3. Cutting Parameters

Cutting Speed V (m/min)	Feed Rate f (mm/rev)	Depth of Cut d (mm)
120	0.025	0.5

ARTIFICIAL NEURAL NETWORKS

In this paper, ANN technique is presented to model the machining performance of Fe-Al alloy. An ANN is a collection of connected units called neurons. The processing ability of the network is stored in the inter-units connection strengths called weights, which are adjusted during training process of the network to minimize error between actual and predicted outputs. The mean squared error (MSE) function is mostly used to assess the deviations. Based upon the architecture, ANNs are classified as feed-forward and feed-backward networks. The first category allows signals to travel from input to output and it is appropriate to formulate equations between a set of input variables and one or more outputs.

Multi-layers perceptron (MLP) is a widely used type of feed-forward networks. A typical MLP network is structured by an input layer, hidden layer and output layer as shown in Fig 2.Neurons in input layer transfer the values of input variables to neurons in the hidden layer.

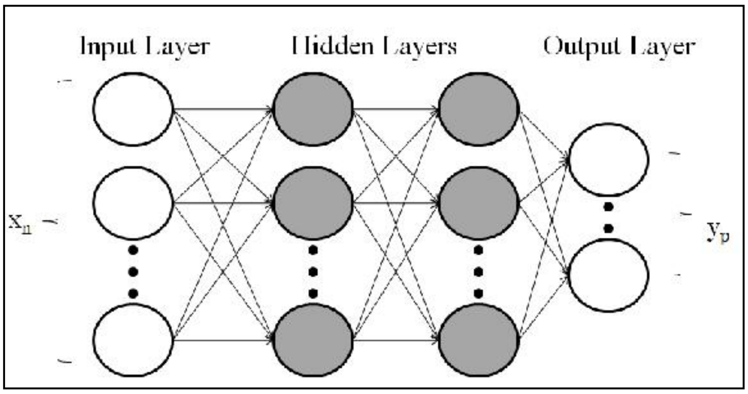

Fig 2: Multi-layers Perceptron Network

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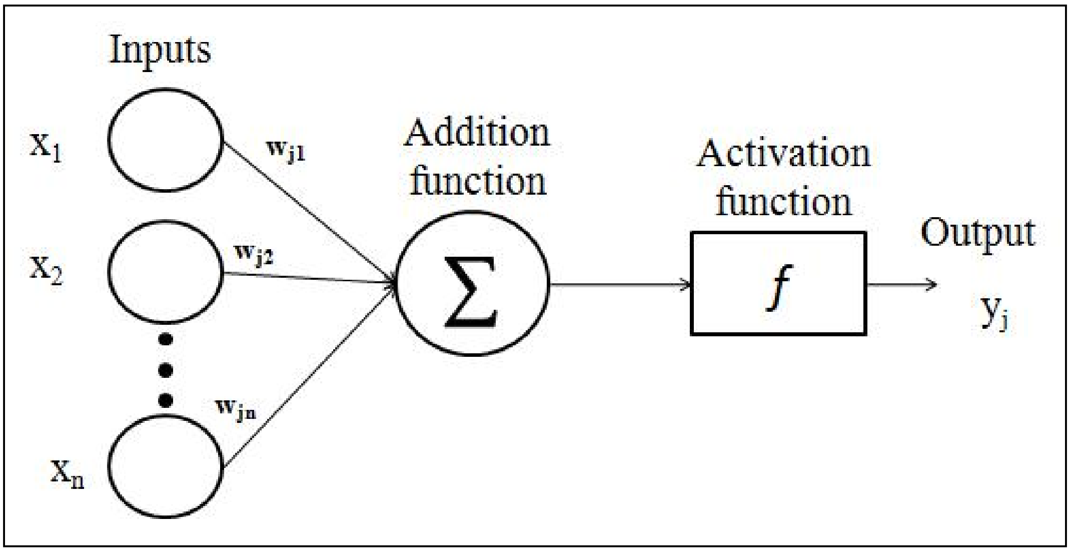

Fig 3: Structure of an artificial neuron

The structure of an artificial neuron j (Fig 3) is characterized by an addition function and an activation function. The addition function eq (1) sums up the input signal after assigning the weights to the connections w_{ji} from the input layer and the neuron is activated by the activation function ‘f’ with a bias b_j (eq.2). The activation function selected in the model is sigmoid as referred in eq.3.

$$S_j = \sum_{i=1}^{n} w_j \, x_i \tag{1}$$

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

$$f(x) = \frac{1}{1 + \exp(-x)} \tag{3}$$

Back propagation algorithm is used to train MLP network to adjust the weights of ANN and minimize the error in predicted values. In the current work, Levenberg-Marquardt back propagation algorithm is chosen. The training process is carried out in two stages viz. forward stage and backward stage. In the forward stage, the weights are assigned to the neural connections and the input values are propagated 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 to diminish the error.

RESULTS AND DISCUSSION

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

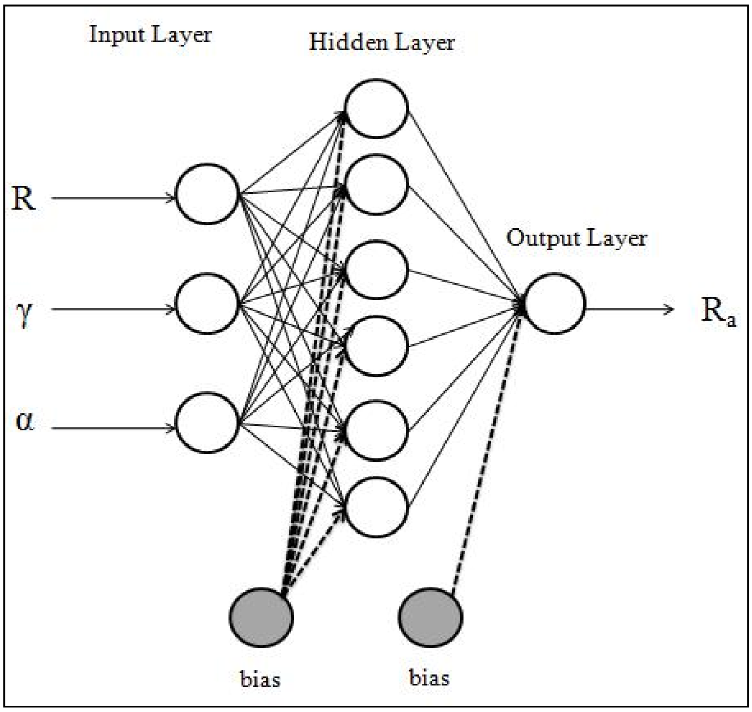

Fig 4: Architecture of the Neural Network

The neural network is trained to minimize the MSE by adjusting the synaptic weights. The performance of the network is successful at epoch 11 with MSE=0.078% as shown in Fig 5. This shows the minimal error between the analytical and experimental outcomes, which is a good sign.

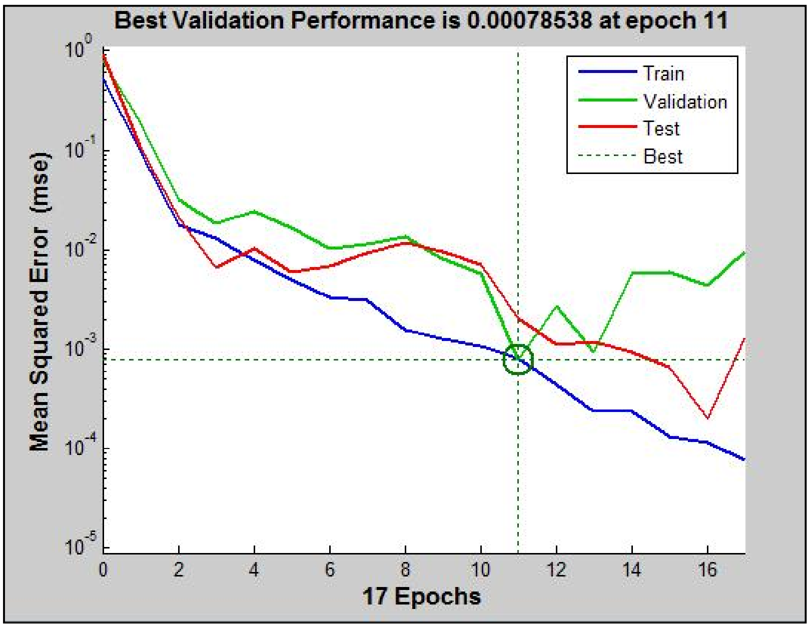

Fig 5: MSE performance plot of the ANN

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 that the reliability of the network is under good control.

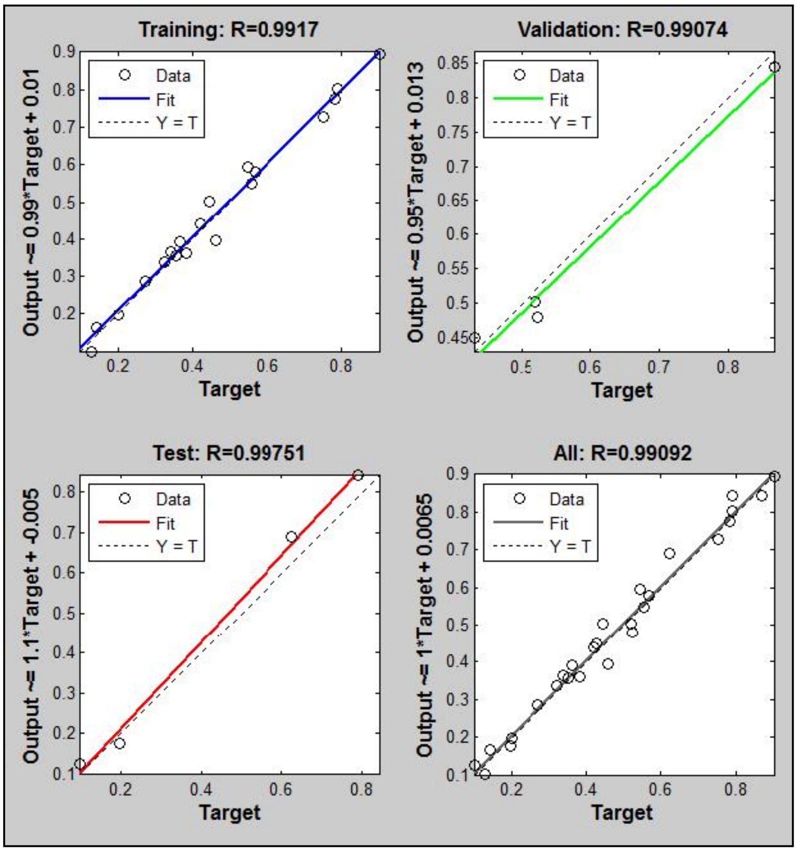

Fig 6: Regression Plots for experimental values versus ANN outputs

The mathematical relation between the input and output variables, which is formulated in the ANN approach is expressed by eq.(4). The activation function f_j (j=1, 2...6) is calculated as shown in eq.(5). The weights w_{j1}, w_{j2} and w_{j3} and biases b_j are enlisted in Table 4.

$$R_a = 0.5587f_1 + 0.6648f_2 - 0.0432f_3 - 0.0293f_4 - 0.5419f_5 - 0.2707f_6 - 0.5534 \quad -(4)$$

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

Table 4. Weights and biases between the input and hidden layer

Neuron j	w_{j1}	w_{j2}	w_{j3}	b_j
1	-2.8376	1.2356	1.5400	5.5360
2	-0.4410	0.6589	-1.2024	-0.0690
3	-1.4508	-3.8935	0.9248	0.5933
4	-1.7612	-2.0250	-0.3572	-0.8592
5	4.1814	0.3461	1.4169	1.7489
6	2.9980	0.2896	-1.3756	2.6455

The ANN outputs are de-normalized to obtain the predicted surface roughness values. They compared with the experimental values as shown in Fig 7. This reveals that the experimental and predicted surface roughness values in all the experiments are in good agreement confirming the fitness of the mathematical model.

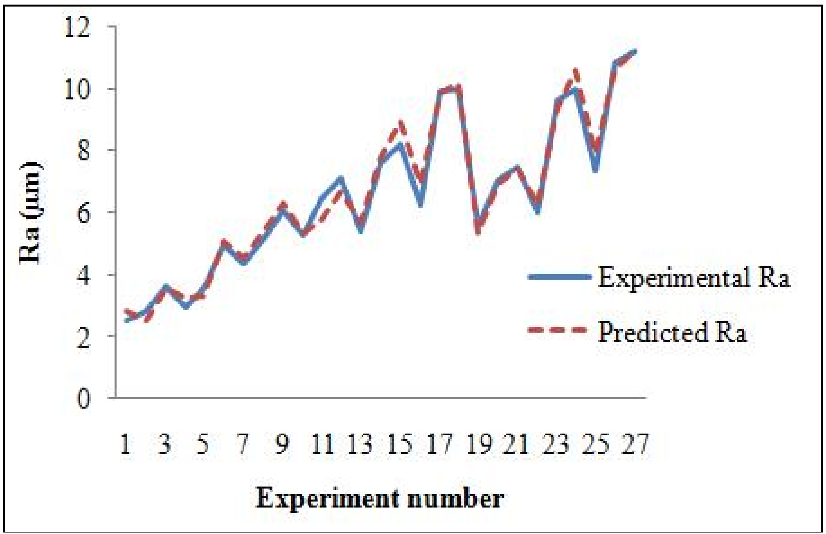

Fig 7: Comparison of experimental and analytical surface roughness values

CONCLUSION

This work is taken up with an objective to remove difficulties associated with machining of Fe-Al alloy and to bring the metal into large scale usage. Proper tool geometry significantly improves the surface finish. Hence, the study is focused on it. Machining experiments are conducted on Fe-Al alloy with variable tool geometry and surface roughness is measured.

Artificial Neural Networks approach is adopted to model the machining performance. Mathematical equation is formulated relating the tool geometry with surface roughness. The fitness of the equation is observed to be reasonably good. Cost of experimentation and time duration are drastically reduced. The model would be useful in the selection of optimum tool geometry that offers improved machining quality. The equation accurately predicts the outcome that is required in production planning and decision making.

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