ANN Based Surface Roughness Prediction In Turning Of AA 6351

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ABSTRACT

Surface roughness is the predominant machining criteria in any machining process and plays a vital role in manufacturing industries. The present work focused on the modeling of surface roughness in turning of AA 6351 alloy with carbide tool. Cutting speed, feed and depth of cut were considered as machining parameters and surface roughness was considered as the response. Experiments were conducted to develop the linear regression equations based on Taguchi's experimental design methodology. Moreover, Artificial Neural Network (ANN) model was also developed for the surface roughness. Further, the performance of the developed model has been tested with the help of ten experimental test cases.

Keywords **–** AA 6351 alloy, turning, multiple regression model, Artificial Neural Network, surface roughness

I. INTRODUCTION

The surface quality is an important parameter to evaluate the productivity of machine tools as well as machined components. Hence, achieving the desired surface quality is of great importance for the functional behavior of mechanical parts. Surface roughness is used as the critical quality indicator for the machined surfaces and it affects the several properties such as wear resistance, fatigue strength, coefficient of friction, lubrication, heat transmission, wear rate and corrosion resistance of the machined parts. Today every manufacturing industry, special attention is given to dimensional accuracy and surface finish. Thus, measuring and characterizing the surface finish can be considered as a predictor for the machining performance.

Grzesik [1] used the minimum undeformed chip thickness to predict surface roughness in turning. Consequently, an existing model for predicting the roughness of a turned surface was improved and the difference between the measurements and predicted results was markedly reduced. Taraman and Lambert [2] developed a mathematical model for surface roughness in terms of cutting speed, feed and depth of cut in turning operation. Then the model used to generate contours of surface roughness in planes containing the cutting speed and feed at different levels of depth of cut. Davim [3] established a correlation between cutting velocity, feed and depth of cut with the surface roughness in turning. Experiments were designed and conducted based on Taguchi technique. The results showed that the cutting velocity had the greater influence, followed by the feed and that the error achieved was smaller than that of a geometric theoretical model. An effort to predict surface roughness in turning of high-strength steel based on RSM was made by Chowdary [4] and observed that the effect of feed is much more pronounced than the effects of cutting speed and depth of cut on the surface roughness. Mathematical model for the surface roughness was developed by Mansour and Abdalla [5] in terms of cutting speed, feed rate and axial depth of cut for the end milling of EN32M steel. Kohili and Dixit [6] proposed a Neural Network based methodology for predicting the surface roughness in turning process on rolled steel bar containing 35% carbon with both HSS and carbide tools with speed, feed, depth of cut and vibration as input parameter. The training data and test data were varied until desired accuracy is reached. Sonar et al. [7] used radial basis neural networks for prediction of surface roughness in turning of mild steel and concluded that radial basis neural networks model are slightly inferior when compared to multilayer perceptron model. Ozel and Karpat [8] developed regression and neural network models for the prediction of surface roughness and tool wear in finished dry hard turning of hardened AISI H-13 steel with cubic boron nitrate tools and observed that neural networks models are superior than regression models.

Abburi and Dixit [9] compared the neural network system and fuzzy sets system and concluded that these types of systems are well suited for modeling the turning operations. Chou and song [10] analyzed effect of tool nose radius on finished turning of hardened AISI52100 steels and observed that large tool nose radii only give finer surface finish, but comparable tool wear compared to small nose radius tools. Chakraburthy and Paul [11] developed a back propagation neural network model for the prediction of surface roughness in turning operation using feed and cutting forces as inputs. Rodrigues et al. [12] investigated the effect of speed, feed and depth of cut on surface roughness (Ra) and cutting force (Fc) in turning of mild steel using HSS tool. Linear regression equations were developed to correlate the effect between the input process parameters and output responses. Khamel et al. [13] investigated the effects of process parameters (cutting speed, feed rate and depth of cut) on performance characteristics (tool life, surface roughness and cutting forces) in finish hard turning of AISI 52100 bearing steel with CBN tool. The combined effects of the process parameters on performance characteristics are investigated using ANOVA. Das et al. [14] investigated the effect of machining parameters such as cutting speed, feed and depth of cut on surface roughness during dry turning of hardened AISI 4340 steel with CVD (TiN+TiCN+Al2O3+ZrCN) multilayer coated carbide inserts. Full factorial design of experiment was used for experimental planning and ANOVA has been employed to analyze the significant machining parameters on surface roughness during turning. The results showed that feed (60.85%) is the most influencing parameter followed by cutting speed (24.6%). Sasimurugan and Palanikumar [15] studied the surface roughness characteristics of hybrid aluminium metal matrix (Al 6061-SiC-Al_2O_3) composites. Feed rate, depth of cut and cutting speed were considered as process parameters and concluded that the surface roughness was increased with the increase of feed rate and decreased with the increase of cutting speed.

II. EXPERIMENTAL WORK

In the present work AA 6351 was machined on CNC lathe LL 20 TL5 by using a carbide cutting tool (CNMG 1204 04 –MF2 1000 T). The chemical composition of AA 6351 is given in Table 1. Taguchi's L_{27} orthogonal array was chosen for the experimental design. Experiments were conducted by varying the cutting parameters and the average surface roughness values (Ra) were measured by using Mituto211 Surf test with a sampling length of 8 mm. The considered cutting parameters and their level are shown in Table 2.

Table 1 Chemical Composition of AA 6351 Alloy (wt%)

Cu	Mg	Si	Fe	Mn
0.1	0.4-0.6	0.7-0.9	0.6	0.4-1.0
Zn	**Ti**	**Cr**	**Al**	
0.1	0.2	0.3	Bal.	

Table 2 Machining Parameters and Their Levels

Machining Parameters	Level 1	Level 2	Level 3
Speed (V)	15	20	25
Feed (f)	0.06	0.09	0.12
Depth of cut (d)	0.45	0.6	0.75

III. METHODOLOGY

Two different types of modeling techniques i.e. multiple linear regression and Artificial Neural Network were used in the present study. The response surface roughness is expressed as a function of cutting parameters i.e. Ra= fun (V, f, d).

Multiple linear regression equation using the cutting parameters speed, feed, depth of cut and their interaction terms is represented as follows:

$$Ra = c_0 + c_1 v + c_2 f + c_3 d + c_4 Vf + c_5 fd + c_6 Vd \quad (1)$$

Where c_0 is the constant and c_1, c_2, c_3, c_4, c_5 and c_6 are the regression coefficients of V, f, d, Vf, Vd and fd respectively.

The ANNs are excellent tools in modeling the machining and manufacturing processes. Most of the time, these techniques have proved better predicted accuracy than the conventional modeling tools. The following paragraphs describe the working principle of the ANN structure. In a multilayer feed-forward network, the processing elements are arranged in layers and only the elements in the adjacent layer are connected. The strength of connection between the two neurons of adjacent layers is expressed by the weight. In the feed-forward network, the weighted connections feed activations only in the forward direction from the input to output layer. Figure 1 shows the structure of a fully connected feed-forward ANN with four layers, one input, two hidden and one output layers of the network.

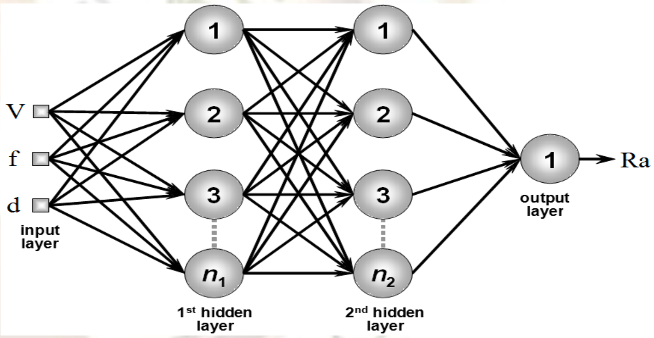

Fig.1 Structure of feed-forward neural network

The number of neurons in the input and output layers is kept fixed depending on the number of inputs and outputs of the system, respectively, whereas the number of neurons in the hidden layer can be varied and optimized for a particular training data set. In the present work 3-10-5-1 ANN architecture was developed.

Each processing elements first performs a weighted accumulation of the respective input values and then passes the result through an activation function. Except for the input layer nodes where no computation is done, the net input to each node is the sum of the weighted output of the nodes in the previous layer.

The output of node j in layer k is

$$net_j^k = \sum w_{ji}^k o_i^{k-1} \quad (2)$$

$$o_j^k = f(net_j^k) = \frac{1}{1+e^{-(net_j^k)}} \quad (3)$$

Where weight W_{kji} is the between the i^{th} neuron in the $(k-1)^{th}$ layer and the j^{th} neuron in the k^{th} layer, $f(x)$ is the activation function and O^{th} is the output of the j^{th} neuron in the k^{th} layer.

IV. RESULTS AND DISCUSSIONS

A. Multiple linear regression model

The measured surface roughness values from experimental data are given in Table 3.

Table 3 Design Matrix and Measured Values of Surface Roughness

Sl. No.	Speed (m/min)	Feed (rev/min)	Depth of cut (mm)	Ra (µm)
1	15	0.06	0.45	0.402
2	15	0.06	0.60	0.43
3	15	0.06	0.75	0.455
4	15	0.09	0.45	0.471
5	15	0.09	0.60	0.485
6	15	0.09	0.75	0.509
7	15	0.12	0.45	0.532
8	15	0.12	0.60	0.55
9	15	0.12	0.75	0.577
10	20	0.06	0.45	0.374
11	20	0.06	0.60	0.397
12	20	0.06	0.75	0.425
13	20	0.09	0.45	0.43
14	20	0.09	0.60	0.441
15	20	0.09	0.75	0.454
16	20	0.12	0.45	0.485
17	20	0.12	0.60	0.5
18	20	0.12	0.75	0.521
19	25	0.06	0.45	0.386
20	25	0.06	0.60	0.401
21	25	0.06	0.75	0.435
22	25	0.09	0.45	0.405
23	25	0.09	0.60	0.432
24	25	0.09	0.75	0.461
25	25	0.12	0.45	0.433
26	25	0.12	0.60	0.44
27	25	0.12	0.75	0.465

For the experimental values regression analysis was done using MINITAB 14 statistical software. The linear regression models were developed using experimental data. Further, the analysis of the models is performed through the significance and ANOVA tests.

The surface roughness in turning of AA 6351 alloy is expressed as a linear function of the input variables and is given in coded form below:

$$Ra = 0.378 - 0.0307\ V + 0.0443\ f + 0.0213\ d + 0.00261\ fd + 0.00139\ Vd \quad (4)$$

A significance test was conducted to determine the effect and contributions of various input cutting parameters and their interaction terms on surface roughness. The results of the significance test are shown in Table 4. The term 'Coef.' in Table 4 represents the coefficient used in Eqn. (4). The term 'SE Coef.' and 'T' gives the standard error for the estimated coefficient and ratio of coefficient value to standard error, respectively. The 'P' value is the minimum value for a preset level of significance at which the hypothesis of equal means for a given factor can be rejected. Considering 95 percent confidence level, the significance of different factors and their interaction terms are tested. Vf is highly correlated with other input variables and hence Vf has been removed from the regression equation. Moreover, the 'P' values of the interaction terms fd and Vd are found to be more than 0.05 and these terms are considered to have no significant contribution to the response, surface roughness. Further, the coefficient of correlation for Ra is found to be equal to 0.89, which provides an excellent relationship between the machining parameters and the response. The results of ANOVA are shown in Table 5. From Table 5, the associated P value for the model is lower than 0.05, indicates that the model is considered to be statistically significant.

Table 4 Significance Test Results

Predictor	Coef	SE Coef	T	P
Constant	0.37752	0.02025	18.64	0.000
V	-0.030722	0.004455	-6.90	0.000
f	0.044333	0.004455	9.95	0.000
d	0.021333	0.004455	4.79	0.000
fd	0.002611	0.004455	0.59	0.564
Vd	0.001389	0.004455	0.31	0.758
S = 0.0189003	R^2 = 89.0%	R^2(adj) = 86.4%		

Table 5 ANOVA Results

Source	DF	SS	MS	F	P
Regression	5	0.06072	0.01214	33.99	0.000
Residual Error	21	0.00750	0.00036		
Total	26	0.06822			

B. Neural networks model

The input layer of ANN consists of three parameters viz. speed, feed and depth of cut and the output layer corresponds to surface roughness. The data were first fed into the network and then simulated to obtain the output. The learning process with 50 epochs and goal of 0 is set for training the surface roughness values and the resultant graph is shown in Figure 2. In Figure 2, MSE is the mean square error and should be minimum.

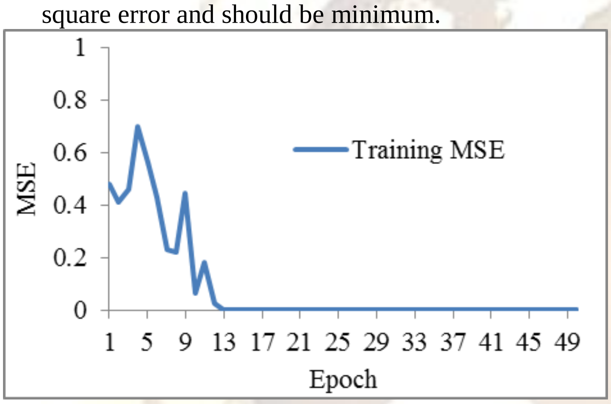

Fig. 2 Performance curve for surface roughness values

Table 4 Experimental test cases

Sl. No.	V	f	d	Exp. Ra	Pre. Ra	Error (%)
1	18	0.06	0.45	0.399	0.379	4.97
2	23	0.09	0.6	0.421	0.432	2.52
3	16	0.12	0.75	0.55	0.575	4.47
4	20	0.1	0.75	0.471	0.466	1.03
5	15	0.08	0.6	0.483	0.473	2.03
6	25	0.11	0.45	0.429	0.419	2.33
7	20	0.09	0.7	0.441	0.450	2.11
8	25	0.06	0.55	0.4	0.398	0.55
9	15	0.12	0.65	0.556	0.562	1.01
10	24	0.07	0.5	0.406	0.401	1.32

The performance of the developed ANN model was tested by ten experimental test cases. Experimental cutting conditions, experimental Ra, predicted Ra and absolute percentage error are presented in Table 4. From the Table 4, it is interesting to note that the average absolute percentage error is found to be equal to 2.24.

Graph between the experimental teat case Ra values and the predicted Ra values was drawn and shown in Fig. 3. From Fig. 3, it is observed that the predicted Ra values are very close to the experimental Ra values. Hence the developed models can be used to predict the surface roughness values in turning of AA 6351 alloy.

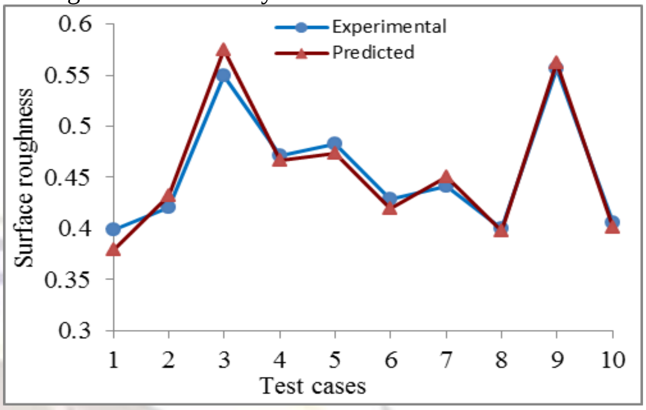

Fig. 3 Experimental vs predicted values for test cases

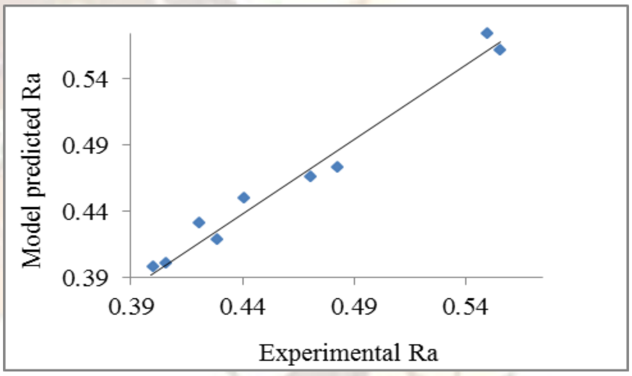

Fig. 4 Scatter plot for test cases

Scatter plot of surface roughness values representing the artificial neural network model is shown in Fig. 4. From Fig. 4, it can be observed that the predicted values are close to the best fit line. The sensitivity analysis of the cutting parameters on the Ra values is shown in Fig. 5. Figure 5 revealed that feed is the major factor that affects the surface roughness followed by speed and depth of cut in turning of AA 6351 alloy.

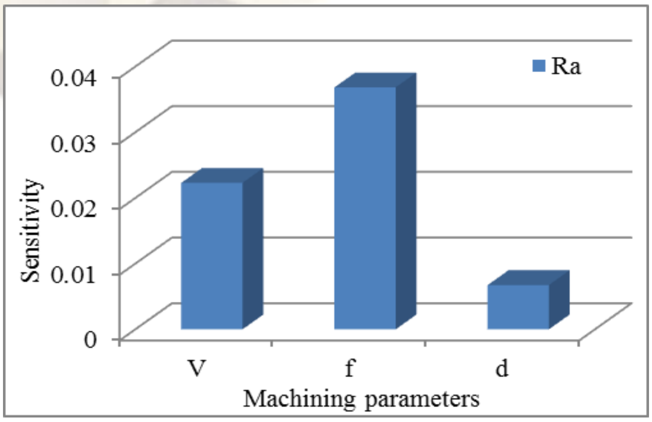

Fig. 5 Sensitivity analysis

V. Conclusion

In the present study, multiple linear regression model and ANN model has been developed for predicting the surface roughness in turning of AA 6351 alloy by using the experimental data. The results of the present work are summarized as follows:

- From the multiple linear regression analysis the interaction terms of speed, feed and depth of cut are not significant on the response surface roughness.
- The average absolute percentage error in predicting the surface roughness values by ANN model is 2.24.
- From the sensitivity analysis feed is the most influenced cutting parameter on the surface roughness followed by speed and depth of cut.

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