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Surface Roughness Prediction Techniques for CNC Turning

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Abstract: This study deals with the development of a surface roughness prediction model for machining aluminum alloys using multiple regression and artificial neural networks. The experiments have been conducted using full factorial design in the design of experiments (DOE) on CNC turning machine with carbide cutting tool. A second order multiple regression model in terms of machining parameters has been developed for the prediction of surface roughness. The adequacy of the developed model is verified by using co-efficient of determination, analysis of variance (ANOVA), residual analysis and also the neural network model has been developed using multilayer perception back propagation algorithm using train data and tested using test data. To judge the efficiency and ability of the model to predict surface roughness values percentage deviation and average percentage deviation has been used. The experimental results show, artificial neural network model predicts with high accuracy compared with multiple regression model.

Key words: Multiple regression, ANOVA and artificial neural networks

INTRODUCTION

The aluminum alloys are used in variety of engineering applications like structural, cryogenic, food processing, oil and gas process industries etc., because of light weight and high tensile strength. The quality of the surface plays a very important role in the performance of turning as a good quality turned surface significantly improves fatigue strength, corrosion resistance, or creep life. Surface roughness also affects several functional attributes of parts, such as, contact causing surface friction, wearing, light reflection, heat transmission, ability of distributing and holding a lubricant, load bearing capacity, coating or resisting fatigue. Therefore, the desired finish surface is usually specified and the appropriate processes are selected to reach the required quality (Mike *et al*., 1998). To achieve the desired surface finish, a good predictive model is required for stable machining. The number of surface roughness prediction models available in literature is very limited (Suresh *et al*., 2002). Most surface prediction models are empirical and are generally based on experiments in the laboratory. In addition, it is very difficult in practice, to keep all factors under control as required to obtain reproducible results (Van Luttervelt *et al*., 1998). Taraman and Lambert (1974) used Response Surface Methodology for prediction of surface roughness. Hasegawa *et al*. (1976) conducted 3^4 factorial desigus to conduct experiments for the surface roughness prediction model. They found that the surface roughness increased with an increase in cutting speed. Sundaram and Lambert (1981) considered six variables i.e., speed, feed, depth of cut, time of cut, nose radius and type of tool to monitor surface roughness.

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Generally these models have a complex relationship between surface roughness and operational parameters, work materials and chip breaker types. In the present study, multiple regression and artificial neural network models have been developed to predict the surface roughness on the machining of aluminum alloys. To judge the efficiency and ability of the model to predict surface roughness values percentage deviation and average percentage deviation were used. The experimental results show, artificial neural network model predicts with high accuracy compared with multiple regression model.

MATERIALS AND METHODS

The work material used for the present investigation is aluminum alloy 6082 cylindrical work pieces. The chemical composition and physical properties of the material used in this study is given in Table 1, 2.

Multiple Regression Model

This study uses statistical multiple regression model for prediction of surface roughness in machining of aluminum alloys, which is used to determine the correlation between a criterion variable and a combination of predicted variables. It can be used to analyze data from any of the major quantitative research designs such as fundamental comparative, correctional and experimental. This method is also able to handle interval ordinal or categorical data and provides estimates both of the magnitude and statistical significance of the relationships between variables (Gall *et al*., 1996). Therefore, multiple regression analysis will be helpful to predict the criterion variable finish surface roughness via predictor variables, such as spindle speed, feed and depth of cut.

Multiple Repression Prediction Model: Formulation

The proposed second order model equation is:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_1 X_2 + \beta_5 X_1 X_3 + \beta_6 X_2 X_3 + \beta_7 X_1^2 + \beta_8 X_2^2 + \beta_9 X_3^2 \tag{1}$$

Where, Y is the estimated response and X_1, X_2 and X_3 are the spindle speed, feed rate, depth of cut, because these are the controllable machining parameters. They can be used to predict the surface roughness which will influence the product qnality, where the coefficients β_0, β_1, β_2............ β_9 are to be estimated. To test the developed model, analysis of variance (ANOVA) is used to investigate and model the relationship between a response variable and one or more independent variables. The independent variables are qualitative (categorical) and no assumption is made about the nature of the relationship (that is, the model does not include coefficients for variables). In order to judge the accuracy of the multiple regression prediction model, percentage deviation (Ø) and the average percentage deviation $(\bar{\phi})$ were used and defined as:

$$\varphi_i = \frac{\left|Ra_i - \widehat{Ra}_i\right|}{Ra_i} \times 100\% \tag{2}$$

Where:

φ_i = Percentage deviation of single sample data

R_{ai} = Actual R_a measured by Profilometer

$\overline{Ra}_i$ = Predicted R_a generated by multiple regression

Table 1: Chemical composition of Aluminum Alloy 6082

Composition	Weight
Cu	0.1 (max)
Mg	0.4-1.2
Si	0.6-1.3
Fe	0.6
Mn	0.4-1.0
Cr	up to 0.25

Table 2: Physical properties of Aluminum alloy 6082

Property	Value
Density	2.70 g cm^{-3}
Melting point	555°C
Modulus of elasticity	70 GPa
Electrical resistivity	0.038×10^{-6} Ω m
Thermal conductivity	180 W m^{-1} K
Thermal expansion	24×10^{-6} K^{-1}

$$\bar{\varphi}=\frac{\sum_{i=1}^{n}\varphi_i}{n}$$

Where:

$\bar{\varphi}$ = Average percentage deviation of all sample data
n = Size of the sample data

This method would test the average percentage deviation of measured R_a and predicted R_a as well as its ability to evaluate the prediction of this model.

Artificial Neural Network Model

Artificial neural networks, which are simplified models of the biological neuron system, is a massively parallel distributing processing system made up of highly interconnected neural computing elements or processing units which are called neurons. Neural networks are built by connecting these neurons together by weighted inter connections. Determination of these weights i.e., training, is the most significant task. In supervised learning the network is trained to learn a mapping from certain inputs to given outputs. An example of supervised learning is the back propagation method for Multi-Layer Perceptron (MLP) networks (Boothroyd and Winston, 1989; Ozel and Karpat, 2002). Multi-layer means the addition of one or more hidden layers in between the input and output layers. In the network each neuron receives total input from all of the neurons in the preceding layer as follows:

$$net_j=\sum_{j=0}^{N}W_{ij}X_i \tag{3}$$

Where:

net_j = Total or net input
N = No. of inputs to the j^{th} neuron in the hidden layer
W_{ij} = Weight of the connection from the i^{th} neuron in the forward layer to the j^{th} neuron in the hidden layer

A neuron in the network produces its output (Out_j) by processing the net input through an activation (Transfer) function f, such as tangent parabolic function given as:

$$Out_j=f(net_j)=\frac{1-e^{-netj}}{1+e^{-netj}} \tag{4}$$

Table 3: Machining parameters and their levels

		Levels		
Control parameters	Symbol	Level 1	Level 2	Level 3
Cutting speed (rpm)	V	1200.0	1350.00	1500.0
Feed rate (mm min^{-1})	f	30.0	50.00	70.0
Depth of cut (mm)	d	0.5	0.75	1.0

Table 4: Experimental Lay out and results of the experimental data

			Experimental values			
V (rpm)	f (mm min^{-1})	d (mm)	1	2	3	Average value (Ra)
1200	30	0.50	1.70	1.74	1.68	1.706
1200	30	0.75	2.26	2.42	2.18	2.286
1200	30	1.00	5.36	5.42	5.40	5.393
1200	50	0.50	2.72	2.78	2.66	2.720
1200	50	0.75	2.36	2.40	2.34	2.366
1200	50	1.00	4.48	4.42	4.46	4.460
1200	70	0.50	2.52	2.56	2.56	2.546
1200	70	0.75	1.62	1.58	1.72	1.640
1200	70	1.00	1.98	2.04	2.00	2.006
1350	30	0.50	3.56	3.66	3.62	3.613
1350	30	0.75	2.54	2.50	2.58	2.540
1350	30	1.00	5.78	5.74	5.80	5.773
1350	50	0.50	2.06	2.14	2.14	2.113
1350	50	0.75	2.04	2.12	2.08	2.080
1350	50	1.00	4.86	4.83	4.92	4.890
1350	70	0.50	1.70	1.78	1.78	1.753
1350	70	0.75	2.26	2.18	2.20	2.213
1350	70	1.00	2.32	2.28	2.40	2.333
1500	30	0.50	2.12	2.20	2.28	2.200
1500	30	0.75	2.98	3.00	3.26	3.080
1500	30	1.00	5.42	5.36	5.51	5.760
1500	50	0.50	3.32	3.26	3.66	3.413
1500	50	0.75	3.68	3.76	3.54	3.660
1500	50	1.00	4.96	4.98	4.93	4.956
1500	70	0.50	2.86	2.77	2.89	2.840
1500	70	0.75	2.68	2.76	2.74	2.726
1500	70	1.00	5.10	4.92	5.00	5.006

Experimental Details

The experiments were conducted according to full factorial design. The three cutting parameters selected for the present investigation are cutting speed (V), feed (f) and depth (d) of cut. Since the considered variables are multi-level variables and their outcome effects are not linearly related, it has been decided to use three level tests for each factor. The machining parameters used and their levels are shown in Table 3.

All the experiments were conducted on CNC Turning Lathe with the following specifications: Swing Over the Bed: 150 mm, Swing Over Cross Slide: 50 mm, Distance Between Centers: 300 mm, Spindle Power 1 HP, Spindle Speed (step less): 0-3000 rpm, Spindle Bore: 21 mm, Spindle Taper: MT3, Tailstock Taper: MT2, the Tool Holder used for Turning operation was a WIDAX tool holder SDJCR 1212 11F3 and the tool material used for the study was Carbide Cutting Tool.

The average surface roughness (R_a) which is mostly used in industrial environments is taken up for the present study. The roughness was measured number of times and averaged. The average surface roughness is the integral absolute value of the height of the roughness profile over the evaluation length and was represented by the following equation.

$$R_a = \frac{1}{L}\int_0^L |Y(x)dx| \tag{5}$$

Where:
L = The length taken for observation
Y = The ordinate of the profile curve

The surface roughness was measured by using Surtronic 3^+ stylus type instrument manufactured by Taylor Hobson with the following specifications. Traverse Speed: 1 mm sec^{-1}, Cut-off values 0.25, 0.80 and 2.50 mm, Display LCD matrix, Battery Alcaline 600 measurements of 4 mm measurement length. The surfaces are cleaned and positioned using a V-block before each measurement. The design matrix (Myers and Montgomery, 1995) and experimental results are shown in Table 4. The experiments were repeated three times and average value was taken up for multiple regression model.

RESULTS AND DISCUSSION

Regression Analysis

The second order multiple regression model for the surface roughness (R_a μm) is developed as a function of cutting parameters such as cutting speed (V), federate (f) and depth of cut (d). From the experimental data for surface roughness, the regression equation was developed and is given as:

$$\begin{aligned} Ra = {} & 28.4-0.0323\times v + 0.044\times f-21.6\times d + 0.000076\times v\times f + 0.00529 \times v\times d- \\ & 0.120\times f\times d + 16.3\times d\times d + 0.000010\times v\times v-0.000820\times f\times f \end{aligned} \tag{6}$$

This analysis is carried out at a significance level of 5% i.e., confidence level of 95%. From the analysis of Table 5 it is evident that, the F-calculated value is greater than the F-table value ($F_{0.05,\,9,\,17}$= 2.49) and hence the second order developed model is quite ample.

The capability of the multiple regression Coefficients for second order model was found to be as 0.851. This shows that the second order model can explain the variation to the extent of 85.1% and P value is less than 0.05 hence model is significant.

Residual Plots for Ra

The regression model is used for determining the residuals of each individual experimental run. The difference between the measured values and predicted values are called residuals. The residuals are calculated and ranked in ascending order. The normal probabilities of residuals are shown in Fig. 1. The normal probability plot is used to vary the normality assumption. As shown in Fig. 1, the data are spread roughly along the straight line. Hence it can be concluded that the data are normally distributed (Shew and Kwong, 2002).

Figure 2 shows the residuals against the observation order. Figure 2 is used to show the correlation between the residuals. From the Fig. 2 it is emphasized that a tendency to have runs of positive and negative residuals indicates the existence of a certain correlation. Also the plot shows that the residuals are distributed eveuly in both positive and negative along the run. Hence the data can be said to be independent.

Figure 3 indicates the residuals versus fitted values, which shows ouly the maximum variation of -1 to 1.5 mm in surface roughness between the measured and the fitted values. This plot does not reveal any obvious pattern and hence the fitted model is ample.

The performance of the developed model was tested using three experimental data which were never used in the modeling process. The results predicted by the multiple regression were compared with the measured values and also average percentage deviation ($\overline{\varphi}$) was calculated and presented in the Table 6.

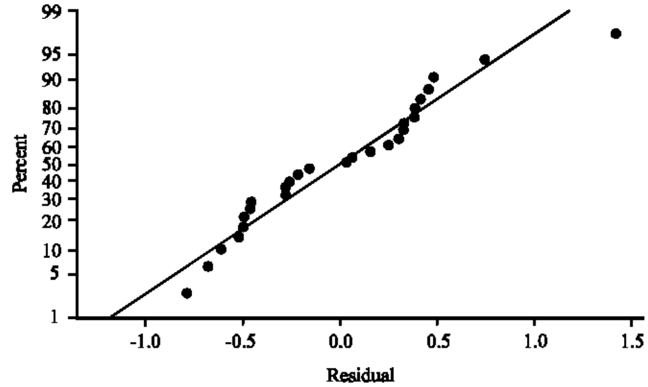

Fig. 1: Normal probability plot of the residuals (Response is R_a)

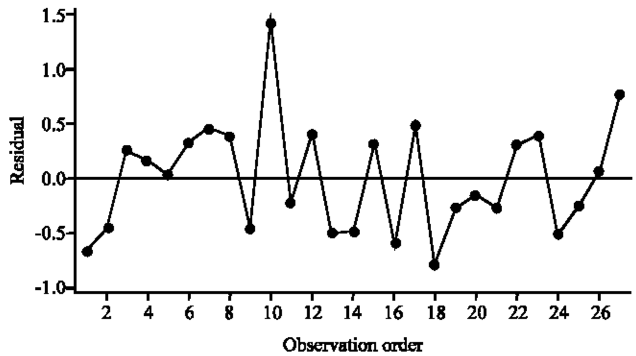

Fig. 2: Residual versus order of the data (Response is R_a)

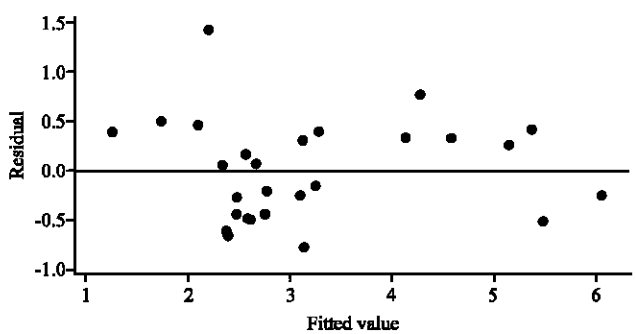

Fig. 3: Residuals versus the fitted values (Response is R_a)

Artificial Neural Network Model

The optimal neural network architecture used in this study is shown in Fig. 4 it was designed using NEURO SOLUTIONS 5.0. The network consists of one input, two hidden and one out put layer. Hidden layers have eight neurons each, where as the input and output layers have three and one neuron, respectively.

Table 5: ANOVA for the response function

Source	df	Seq SS	Adj SS	Adj MS	F-value	p-value
Regression	9	38.7530	38.7530	4.30589	10.79	0.0000
Residual error	17	6.7829	6.7829	0.39899		
Total	26	45.5359				

Table 6: Comparison of the predicted and measured results as a percentage deviation (using Multiple Regression)

Parameters			Surface roughness		
V	f	d	Measured	Predicted	Deviation (%)
1233	37	0.50	2.306	2.066	10.40
1500	35	0.89	4.176	3.987	4.50
1306	53	0.50	2.390	2.118	11.38

Avg. deviation: 8.76%

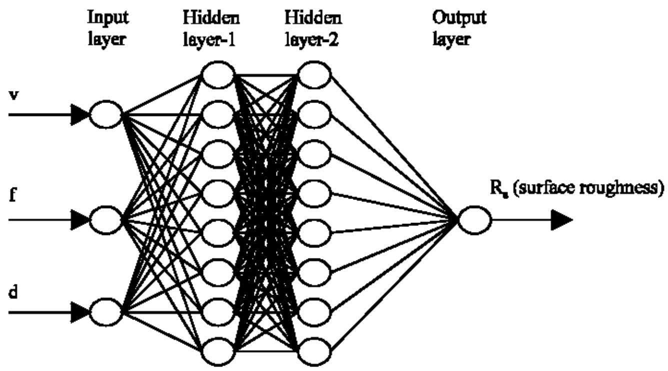

Fig. 4: Neural network architecture designed

Since surface roughness prediction in terms of cutting speed, feed and depth of cut was the main interest in this research, neurons in the input layer as shown in Fig. 4 corresponding to the cutting speed, feed and depth of cut the output layer corresponds to surface roughness.

Generation of Training Data

To calculate the connection weights, a set of desired network output values are needed. Desired output values are called the training data set. The training data set in this study was created using full factorial design in the design of experiments (DOE). The surface roughness values corresponding to the training data were measured at different locations and average value was taken. This is the most common experimental design. A three level full factorial design creates 3^n training data, where n is the number of variables (n = 3). In this study $3^3 = 27$ training data were used. The range of process variables are shown in Table 3.

Network Training

Calculation of weights to the variables is called network training. The weights are given quasi-random, intelligently chosen initial values. They are then iteratively updated until convergence takes place i.e. minimize the Mean Square Error (MSE) between the network prediction and training data set as shown below.

$$W_{ij}^{new} = W_{ij}^{old} + \Delta W_{ij}$$

$$\Delta W_{ij} = -\eta \frac{\partial E}{\partial W_{ij}} out_j$$

Table 7: Comparison of the predicted and measured results as a percentage deviation (Using artificial neural network model)

Parameters			Surface roughness		
V	f	d	Measured	Predicted	Deviation (%)
1233	37	0.50	2.306	2.3049	0.045
1500	35	0.89	4.176	4.2101	0.802
1306	53	0.50	2.390	2.3951	2.090

Avg. deviation: 0.9853%

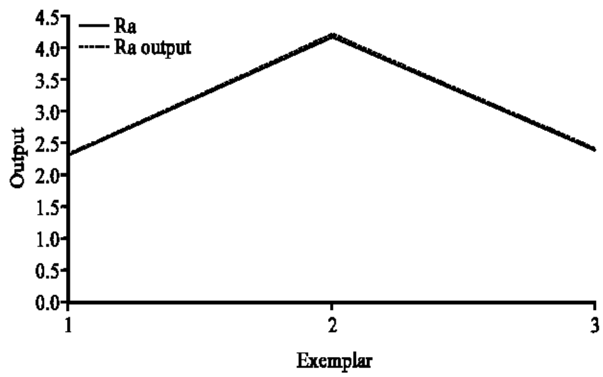

Fig. 5: Desired out put and actual network output

Where:

E = Mean square error and out_j is the j^{th} neuron output

η = Learning rate [step size, momentum] parameter

The learning rate [step size 1.0, momentum 0.7] selected and the training process takes place for 50,000 training iterations. The MSE calculated for training data is 0.0003.

The Fig. 5 shows the measured output i.e. measured Surface Roughness and network predicted Surface Roughness.

Neural Network Testing

Once the weights are adjusted the performance of the trained network should be tested using three experimental data which were never used in the training process. The results predicted by the network were compared with the measured values and percentage deviation (Ø) has been calculated and shown in the Table 7.

CONCLUSIONS

Using full factorial design in the design of experiment, the machining parameters which are influencing the surface roughness on the machining of Al Alloys has been modeled using Multiple Regression and Artificial Neural Networks.

- The Multiple Regression Model is developed to predict the Surface Roughness for Turning of Al Alloys and the predicted model was tested with three sets which were never used in modeling and average percentage deviation calculated as 8.76%.
- The neural network model is developed to predict surface roughness and predicted model was tested using the same test data which were used in Multiple Regression Model and the Average Percentage Deviation was calculated as 0.9853%.

- After analyzing the Multiple Regression Model and Artificial Neural Network Model, the Artificial Neural Network Model has good prediction capability and has given minimum percentage deviation compared to the Multiple Regression Model.

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