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Modeling of Machining Parameters in CNC End Milling Using Principal Component Analysis Based Neural Networks

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Abstract

The present paper uses the principal component analysis (PCA) based neural networks for predicting the surface roughness in CNC end milling of P20 mould steel. For training and testing of the neural network model, a number of experiments have been carried out using Taguchi's orthogonal array in the design of experiments (DOE). The cutting parameters used are nose radius, cutting speed, cutting feed, axial depth of cut and radial depth of cut. The accurate mathematical model has been developed using PCAs networks. The adequacy of the developed model is verified using coefficient of determination (R). It was found that the R^2 value is 1. To judge the ability and efficiency of the neural network model, percentage deviation and average percentage deviation has been used. The research showed acceptable prediction results for the neural network model.

Keywords: PCA based neural networks, DOE, P20mould steel.

1. Introduction

The Pre-hardened steel (P-20) is widely used material in production of molds/dies because of less wear-resistant and are used for large components. Milling is the most common form of machining process used in the production of moulds/dies, due to the high tolerances and surface finishes by cutting away the unwanted material. A serious attention is given to accuracy and surface roughness of the product by the industry these days. Surface finish has been one of the important considerations in determining the machinability of materials. Surface roughness and dimensional accuracy have been important factors to predict machining performances of any machining operation. In the past, Abbas Fadhel Ibraheem *et al*. (2008) investigated the effect of cutting speed, feed, axial and radial depth of cut on cutting force in machining of modified AISI P20 tool steel in end milling process. They concluded that, higher the feed rates, larger the cutting forces. They also developed the genetic network model to predict the cutting forces. Abou-El-Hossein *et al*. (2007) developed the model for predicting the cutting forces in an end milling operation of modified AISI P20 tool steel using the response surface methodology. Rahman *et al*. (2001, 2002) compared the machinability of the P20 mould steel (357 HB) in dry and wet milling conditions. They considered a range of 75–125 m/min for the cutting speed and a feed ranging between 0.3 and 0.7 mm/tooth:

they found the cutting forces in both processes to be similar, but with the flank wear acceleration higher in dry milling. Furthermore, they observed a better surface finish with wet milling. Liao & Lin (2007) studied the milling process of P20 steel with MQL lubrication. The cutting speeds were from 200-500m/min and the feed between 0.1-0.2mm/tooth. The authors found that the tool life is higher with MQL, due to an oxide layer formed on the tool inserts that helped to lengthen the tool life. Saurav Datta *et al*. (2010) optimized the CNC end milling process parameters for surface finish and material removal rate using PCA based Taguchi method.

In the present work, an attempt has been made to develop the PCA based artificial neural network model to predict the surface roughness in end milling of P20 steel by considering the input parameters such as nose radius, cutting speed, feed rate, axial-depth of cut, and radial depth of cut. The developed model is tested using test data. The predicted results were analyzed through experimental verification. To have more precise investigation into the model, a regression analysis of experimental and predicted outputs was preformed. It was found that the R^2 value is 1. To judge the ability efficiency of the developed model, percentage deviation and average percentage deviation has been used.

2. Materials and Methods

The workpiece material used for the present investigation is P20 mould steel of flat work pieces of 100 mm ×100mm ×10mm and the density of the material in metric units is 7.8 g / cc. The chemical composition of the workpiece material is given in the Table 1.

2.1 Principal component analysis based neural networks

Principal component analysis networks (PCAs) combine unsupervised and supervised learning in the same topology. PCA is an unsupervised linear procedure that finds a set of uncorrelated features, principal components, from the input. The unsupervised segment of the network performs the feature extraction and the supervised segment of the network performs the (linear or nonlinear) classification of these features using a multi layer perceptron (MLP). Multilayer 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 according to Eq. (1).

$$net_j = \sum_{j=0}^{N} W_{ij} X_i \tag{1}$$

Where net_j is the total or net input and N is the number of inputs to the j^{th} neuron in the hidden layer. W_{ij} is the weight of the connection from the i^{th} neuron in the forward layer to the j^{th} neuron in the hidden layer. The sum of modified signals (total activation) is then modified by a tangent hyperbolic transfer function as in Eq. (2). Batch mode type of supervised learning has been used in the present case.

$$Out_j = f(net_j) = \frac{1 - e^{-netj}}{1 + e^{-netj}} \tag{2}$$

The learning rule choices for PCA are Sangers and Ojas. They are both normalized implementations of the Hebbian learning rule. Between the two, Sanger's is preferred for PCA because it naturally orders the PCA components by magnitude. This also provides an easy way to decide if the number of PCA components is reasonable—simply check the ratio of the first component magnitude versus the last component magnitude. Since this network is a hybrid supervised-unsupervised network, the control parameters must be set for both the supervised and the unsupervised segments of the network. If the network has p inputs (it is assumed that the samples have p components) and m<p linear output processing elements. The output is given by Eq. (3).

$$y_i(n) = \sum_{i=0}^{p-1} w_{ij}(n) x_i(n) \quad j = 0,1............, m-1 \tag{3}$$

To train the weights, the following modified Hebbian rule is used in unsupervised learning.

$$\Delta w_{ji}(n) = \eta \left[y_j(n) x_i(n) - y_j(n) \sum_{k=0}^{j} w_{ki}(n) y_k(n) \right] \quad i = 0,1....., p-1; j = 0,1......, m-1 \tag{4}$$

Where η is the step size.

3. Experimental Details

A detailed survey has been carried out to find out how machining parameters affect surface rourhness of P20 mould steel material (Rahman, 2001, 2002; Saurav Datta, 2010). Based on this, the five parameters, namely nose radius, cutting speed, feed rate, axial depth of cut and radial depth of cut were selected for experimentation.Taguchi's $L_{50}\,(2^1{*}5^{11})$ orthogonal array in design of experiments (DOE) technique has been implemented to conduct the experiments. Nose radius with two levels and cutting speed, cutting feed, axial depth of cut and radial depth of cut with five levels each and then 2×5×5×5×5=1250 runs were required in the experiments for five independent variables. But using Taguchi's orthogonal array, the number of experiments reduced to 50 experiments from 1250 experiments. All the experiments were conducted on CNC Vertical milling machine 600 II as shown in Figure 1. The specifications of the Vertical milling machine are: The tool holder used for milling operation was KENAMETAL tool holder BT40ER40080M, Table clamping area: 20 TOOLS ATC STANDARD, Maximum load on the table: 700 kgs, Spindle taper: BT-40, Spindle speeds range: 8-8000rpm, Power: 13 kW, Feed rates range: 0-12 m/min and the too material used for the present study was coated carbide cutting tool. The machining parameters used and their levels chosen are presented in Table 2.

The average surface roughness (R_a, μm) which is mostly used in industrial environments is taken up for the present study. 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 Eq. (5).

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

Where L is the length taken for observation and Y is 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: 1mm/sec, Cut-off values 0.25mm, 0.80mm and 2.50mm, Display LCD matrix, Battery Alcaline 600 measurements of 4 mm measurement length. The experimental layout and results are given in Table 3.

4. Development of PCA based NN model for predicting the surface roughness

The five principal components are given as input to neural network and output is surface roughness. Now network has been trained by varying the number of neurons in hidden layer to study the network performance. Each of them is trained separately, and the best network is selected based on the accuracy of the predictions in the testing phase. The general network is supposed to be 5-n-1, which implies 5 neurons in the input layer, n neurons in the hidden layer and one neuron in the output layer. The performance of the network is checked with the means square error. If the mean square error is more than a prescribed limiting value, it is back propagated from output to input, and weights are further modified till the error or number of iteration are within a prescribed limit. The Mean square error (MSE) for pattern *p* is defined as in Eq. (6).

$$MSE = \sum_{i=1}^{n} \frac{1}{2}\left(D_{Pi} - O_{Pi}\right)^2 \tag{6}$$

Where D_{pi} is the target output, and O_{pi} is the computed output for the i^{th} pattern.

The performance of the network for different neurons is show in Figure 2. In this study 5-13-1 was selected which has the minimum mean square error. It was designed using NeuroSolutions 4.0 software**.** The network consists of one input, one hidden and one output layer. The input layer has 5 neurons, hidden layer has thirteen neurons and output layer has one neuron respectively. Since surface roughness prediction in terms of nose radius, cutting speed, cutting feed, axial depth of cut and radial depth of cut was the main interest in this research, neurons in the input layer corresponding to the nose radius, cutting speed, cutting feed, axial depth of cut and radial depth of cut, the output layer corresponds to surface roughness.

4.1 Generation of Train and Test 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 Taguchi's L_{50} orthogonal array in the design of experiments. In this study, 50 data set were used for training and 7 data set were used for testing the network respectively and is given in Table 3 and Table 4.

4.2 Neural network training

For calculation of weight variables, often referred to as network training, the weights are given quasi-random, intelligently chosen initial values. They are then iteratively updated using momentum learning method so as to minimize the mean square error (MSE) between the network prediction and training data set as in Eq. (7) and Eq.(8).

$$W_{ij}^{new} = W_{ij}^{old} + \Delta W_{ij} \quad (7)$$

$$\Delta W_{ij} = -\eta \sum_{t=1}^{k} \alpha^{k-t} \frac{\partial E}{\partial W_{ij}} out_j \quad (8)$$

Where E is the MSE and out_j is the j^{th} neuron output. η is the learning rate [step size, momentum] parameter controlling the stability and rate of convergence of the network.. The learning rate [step size 1.0, momentum 0.7] selected and the training process takes place on a Genuine Intel x86 Family 6 Model 14 Stepping 12 ~17 processor PC for 60,000 training iterations. The minimum mean square error is obtained after training of the network with 49805 epochs for training data is 2.23683E-11. Figure 3 depicts the convergence of minimum MSE with epochs. The comparison between ANN model output and experimental output for training data sets are shown in Figure 4. Figure 4 showing that, the predicted values using ANN is very good correlation and representation with the experimental results.

In order to judge the ability and efficiency of the model to predict the surface finish values percentage deviation (Ø) and the average percentage deviation ($\bar{\phi}$) were used and calculated as in Eq. (7) and Eq. (8)

$$\phi_i = \frac{|\text{Experimental} - \text{Predicted}|}{\text{Experimental}} \times 100\% \quad (9)$$

Where ϕ_i = percentage deviation of single sample data

$$\bar{\phi} = \frac{\sum_{i=1}^{n} \phi_i}{n} \quad (10)$$

Where $\bar{\phi}$ = average percentage deviation of all sample data and n= size of the sample data. The percentage deviation is shown in Figure 5. The maximum, minimum and average percentage deviation for surface roughness of training data were found as 0.002047%, -0.00272% and 0.000064% respectively.

4.3 Neural network testing

The ANN predicted results are in very good agreement with experimental results and the network can be used for testing. Hence the testing data sets are applied for the network, which were never used in the training process. The results predicted by the network were compared with the measured values and shown in Figure 6. The average percentage deviation for test data was found to be 3.945808%.

4.4 Regression Analysis

To have more precise investigation into the model, a regression analysis of predicted and measured values was performed and is shown in Figure 7. The adequacy of the developed model is verified by using coefficient of determination (R^2). $0 \le R^2 \le 1$. The R^2 is the variability in the data accounted for by the model in percentage [8].

The regression coefficient is calculated to estimate the correlation between the predicted values by the ANN model and the measured values resulted from experimental tests. The regression coefficient is calculated by using Eq. (11).

$$R^2 = 1 - \left[\frac{\sum_j (t_j - o_j)^2}{\sum_j (o_j)^2} \right] \quad (11)$$

Where t_j= targets or experimental values or measured values; o_j= outputs or predicted values.

There is a high correlation between the predicted values by the ANN model and the measured values resulted from experimental tests. The correlation coefficient for surface roughness was 1, which shows there is a strong correlation in modeling surface roughness. From Figure 7, it is very difficult to distinguish the best linear fit line from the perfect line, because the fit is so good.

5. Parametric Analysis

The sensitivity test was performed to obtain the variables that affect the surface roughness as shown in Figure 8. The test shows that feed rate is the most significant effect parameter on surface roughness followed by radial depth, nose radius, axial depth, and cutting speed. The variation of surface roughness for varied inputs is shown in Figure 9-13. It is concluded that, the surface roughness increases with the increase of nose radius, cutting feed and axial depth of cut, because the increase of feed rate and axial depth of cut increased the heat generation and hence, tool wear which resulted in the higher surface roughness. The increase in federate also increased the chatter and produced incomplete machining at a faster traverse which led to higher surface roughness. The surface roughness decreases as the cutting speed and radial depth of cut increases.

6. Conclusions

Using Taguchi's orthogonal array design in the design of experiments, the machining parameters which are influencing the surface roughness in end milling of P20 mould steel has been modeled using PCA based neural networks. Based on experimental and ANN results, the following conclusions are drawn.

- The PCA based ANN predicted values are fairly close to the experimental values, which indicates that the developed model can be effectively used to predict the surface roughness of P20 mould steel.
- The feed rate is the most significant effect parameter on surface roughness followed by radial depth, nose radius, axial depth, and cutting speed.
- The ANN model could predict the surface roughness with average percentage deviation of 0.000064%from training data set.
- The ANN model could predict the surface roughness with average percentage deviation of 3.945808% from test data set.
- The correlation coefficient for surface roughness was 1, which shows there is a strong correlation in modeling surface roughness.

References

Abbas Fadhel Ibraheem, Saad Kareem Shather, Kasim A. Khalaf (2008), "Prediction of Cutting Forces by using Machine Parameters in end Milling Process", *Eng. & Tech.* **26** (11), 1-4.

Abou-El-Hossein, K.A., Kadirgama, K., Hamdi, M., Benyounis, K.Y. (2007), "Prediction of cutting force in end-milling operation of modified AISI P20 tool steel". *J Mater Process Technol* **182** (1–3), 241–247.

Rahman, M., Senthil Kumar, A., & Salam, M.U. (2002), "Experimental evaluation of the effect of minimal quantities of lubricant in milling", *Int. J. Machine Tools and Manuf*., **42**(5), 539–547.

Rahman, M., Senthil Kumar, A., and Salem Manzoor, U.I. (2001), "Evaluation of minimal quantities of lubricant in end milling", *Int. J. Advanced Manuf. Tech.*, **18**(4), 235–241.

Liao, Y.S., and Lin, H.M., (2007), "Mechanism of minimum quantity lubrication in high-speed milling of hardened steel", *Int. J. Machine Tools and Manuf*., **47**(11), 1660–1666.

Sanjit Moshat, Saurav Datta, Asish Bandyopadhyay & Pradip Kumar Pal (2010), **"**Optimization of CNC end milling process parameters using PCA-based Taguchi method", *International Journal of Engineering, Science and Technology*, **2(**1), 92-102.

Neurosolutions 4.0 documentation available at http://www.neurosolutions.com/downloads/documentation.html.

Montgomery, D.C. (2001), "*Design and analysis of Experiments*", (fifth ed.). Wiley, New York.

Table 1. Chemical composition of P20 mould steel

Composition	Weight (%)
Carbon	0.35-0.45
Silicon	0.2-0.4
Manganese	1.3-1.6
Chromium	1.8-2.1
molybdenum	0.15-0.25

Table 2. Machining parameters and their levels

Machining parameter	Units	Symbol	Level1	Level2	Level3	Level4	Level5
Nose radium	mm	R	0.8	1.2	-	-	-
cutting speed	m/min	V	75	80	85	90	95
feed rate	mm/tooth	f	0.1	0.125	0.15	0.175	0.2
Axial depth of cut	mm	d	0.5	0.75	1	1.25	1.5
Radial depth of cut	mm	rd	0.3	0.4	0.5	0.6	0.7

Table 3. Experimental Layout and results of the experimental data.

S. NO	R	V	f	d	rd	*Ra*	S. NO	R	V	f	d	rd	*Ra*
1	1	1	1	1	1	*0.94*	26	2	1	1	1	4	*0.98*
2	1	1	2	2	2	*1.16*	27	2	1	2	2	5	*1.2*
3	1	1	3	3	3	*1.12*	28	2	1	3	3	1	*1.68*
4	1	1	4	4	4	*0.86*	29	2	1	4	4	2	*1.06*
5	1	1	5	5	5	*0.66*	30	2	1	5	5	3	*0.52*
6	1	2	1	2	3	*0.82*	31	2	2	1	2	1	*1.14*
7	1	2	2	3	4	*1.44*	32	2	2	2	3	2	*2.48*
8	1	2	3	4	5	*0.7*	33	2	2	3	4	3	*1.74*
9	1	2	4	5	1	*0.92*	34	2	2	4	5	4	*1.48*
10	1	2	5	1	2	*1.28*	35	2	2	5	1	5	*1.72*
11	1	3	1	3	5	*1.08*	36	2	3	1	3	3	*0.52*
12	1	3	2	4	1	*1.3*	37	2	3	2	4	4	*0.92*
13	1	3	3	5	2	*1.48*	38	2	3	3	5	5	*0.76*
14	1	3	4	1	3	*1.44*	39	2	3	4	1	1	*0.64*
15	1	3	5	2	4	*1.54*	40	2	3	5	2	2	*0.96*
16	1	4	1	4	2	*0.56*	41	2	4	1	4	5	*0.8*
17	1	4	2	5	3	*0.46*	42	2	4	2	5	1	*0.5*
18	1	4	3	1	4	*0.42*	43	2	4	3	1	2	*1.54*
19	1	4	4	2	5	*0.58*	44	2	4	4	2	3	*1.27*
20	1	4	5	3	1	*0.5*	45	2	4	5	3	4	*1.32*
21	1	5	1	5	4	*0.46*	46	2	5	1	5	2	*0.87*
22	1	5	2	1	5	*1.1*	47	2	5	2	1	3	*1.1*

23	1	5	3	2	1	*0.86*	48	2	5	3	2	4	*0.78*
24	1	5	4	3	2	*0.48*	49	2	5	4	3	5	*1.14*
25	1	5	5	4	3	*0.74*	50	2	5	5	4	1	*0.87*

Table 4. Data set used in testing ANN model

S. NO	R	V	f	d	rd	Ra
1	0.8	87	0.14	1.35	0.6	0.66
2	0.8	87	0.16	0.8	0.6	0.54
3	1.2	78	0.16	1.35	0.4	1.2
4	1.2	78	0.16	0.8	0.6	1.56
5	1.2	78	0.14	1.35	0.6	1.06
6	1.2	87	0.16	0.8	0.4	1.38
7	1.2	87	0.14	0.8	0.6	1.14

Figure 1. Vertical milling machine 600 II

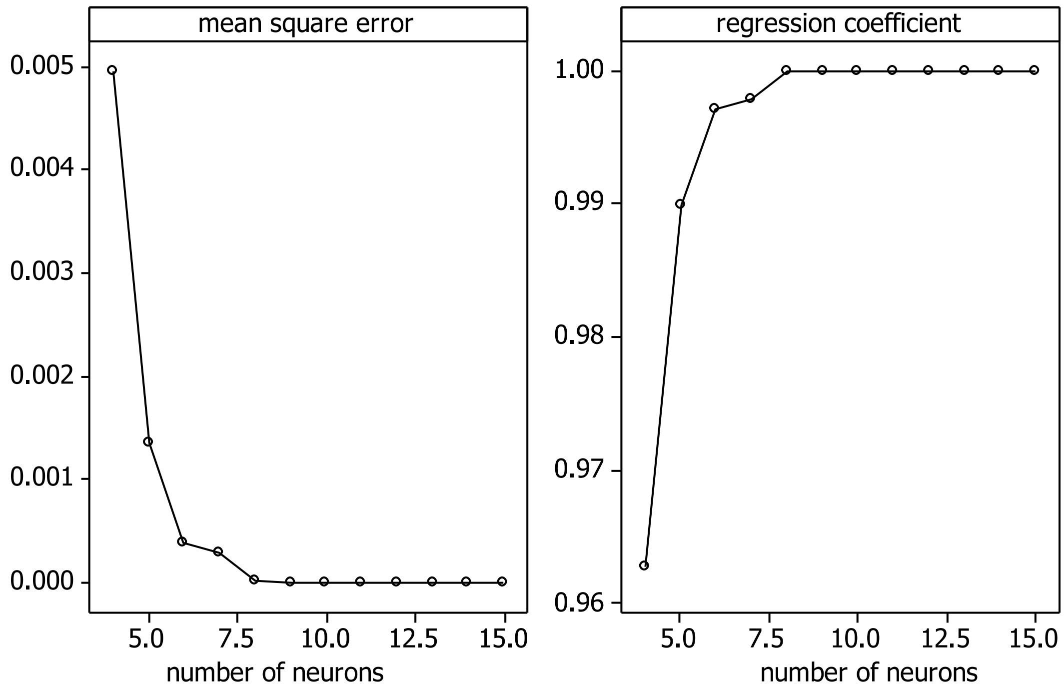

Figure 2. Performance of the network

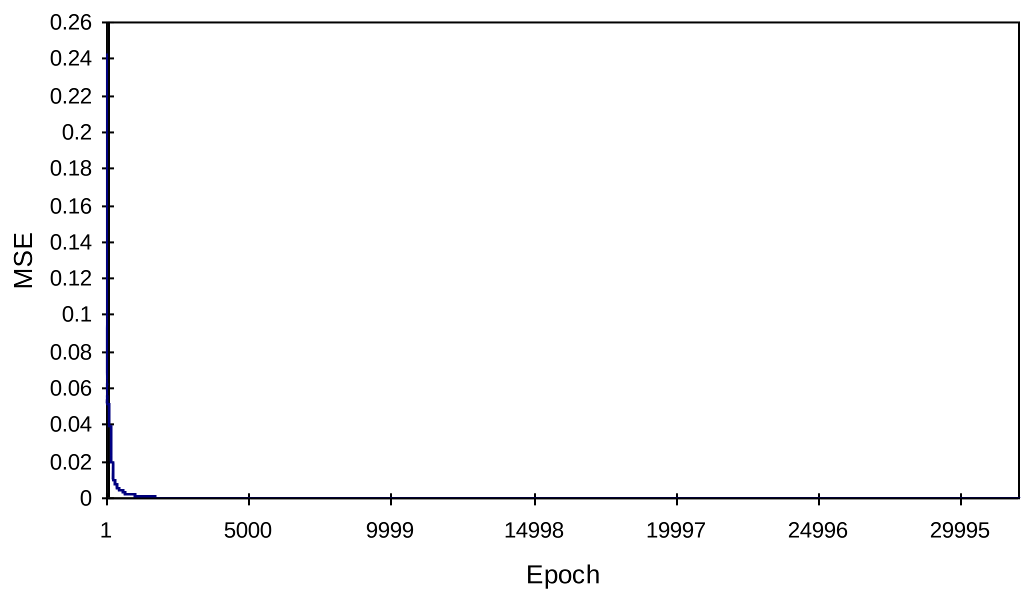

Figure 3. Learning behavior of ANN model for surface roughness

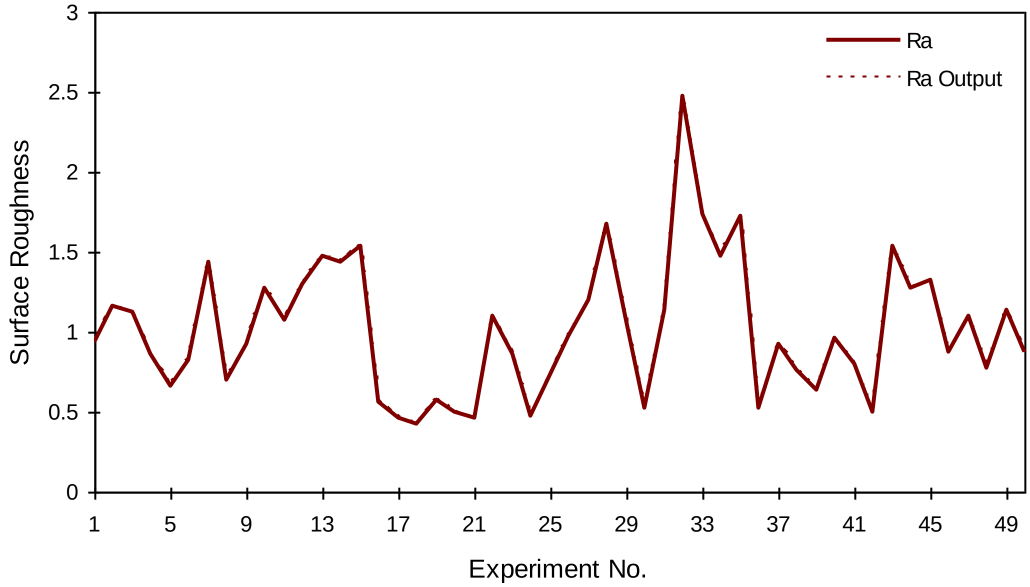

Figure 4. Comparison of Experimental and ANN output for surface roughness

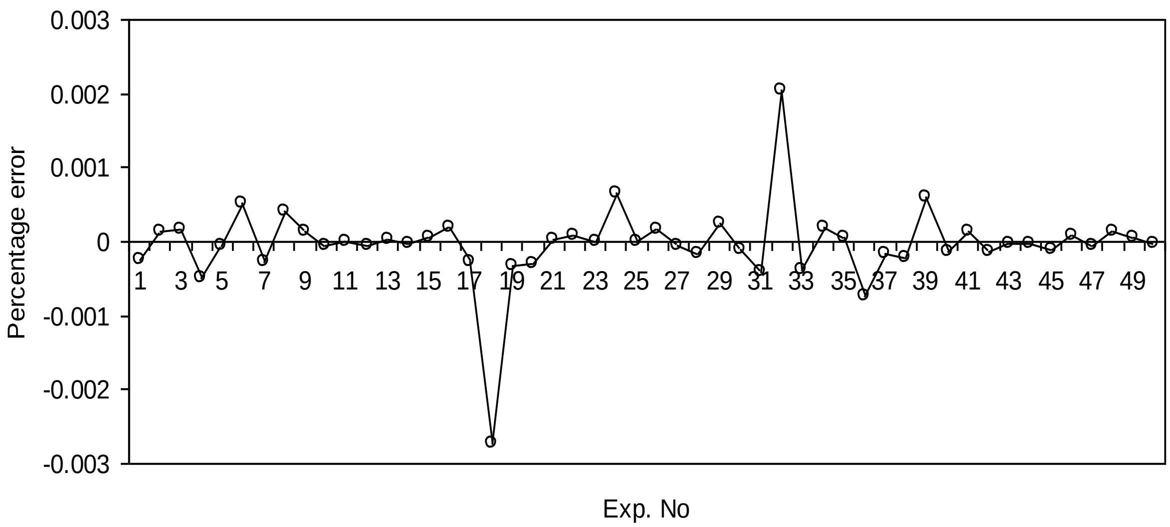

Figure 5. Percentage deviations of surface roughness (Training)

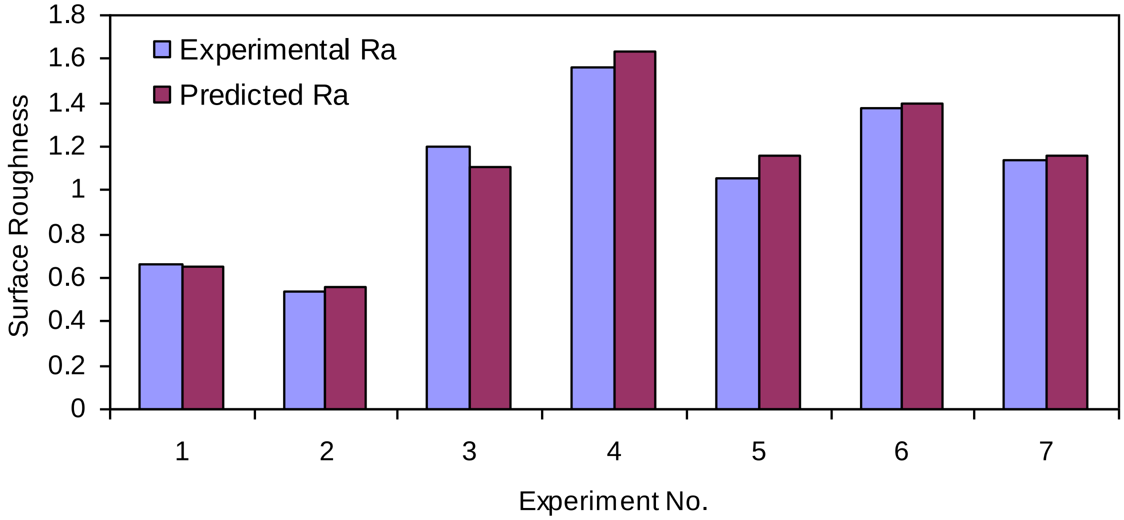

Figure 6. Verification Test results for surface roughness

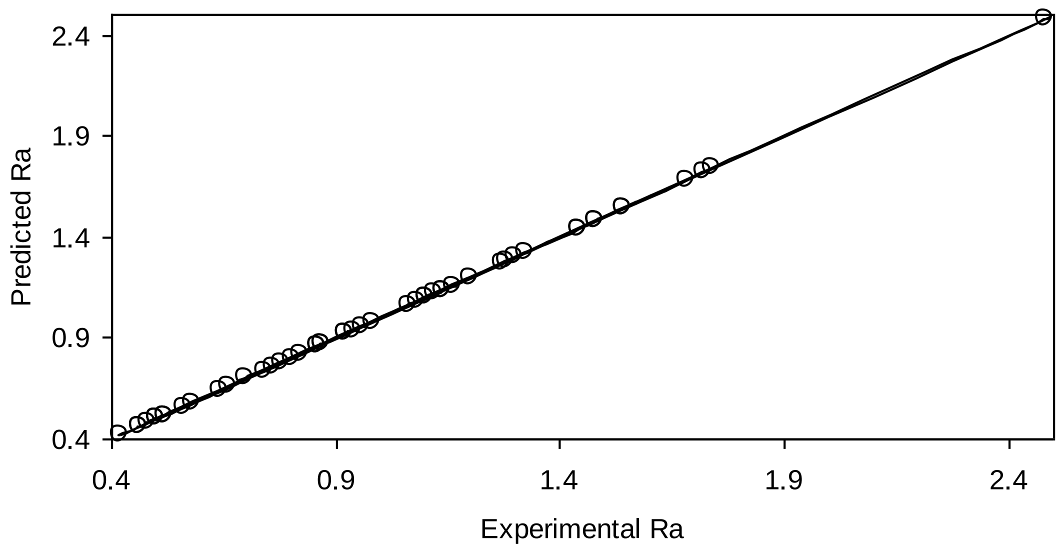

Figure 7. Predicted outputs Vs measured outputs

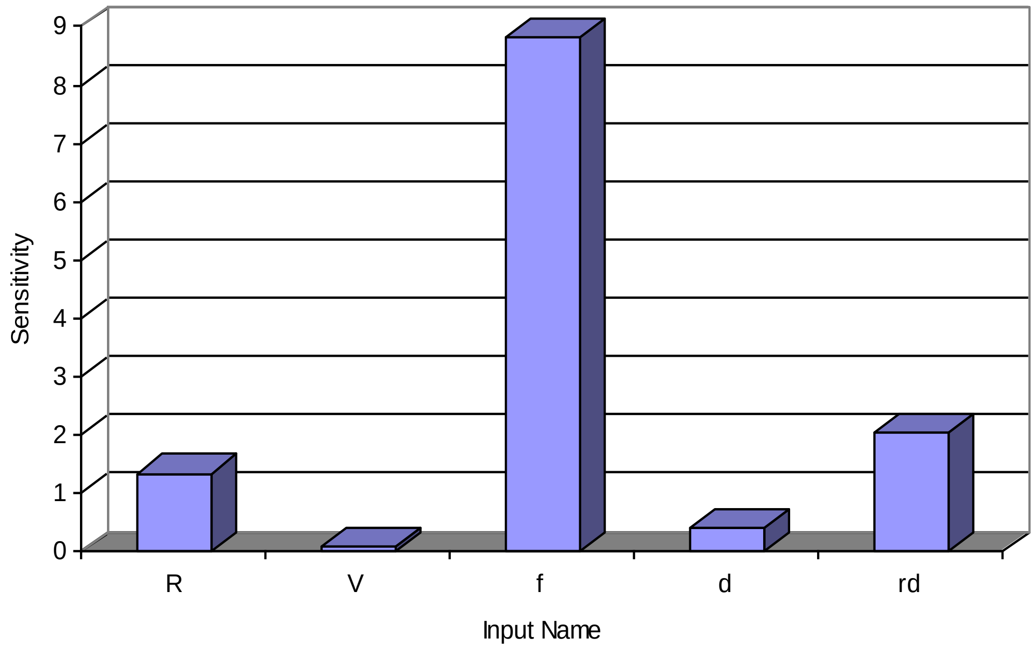

Figure 8.SensityTest

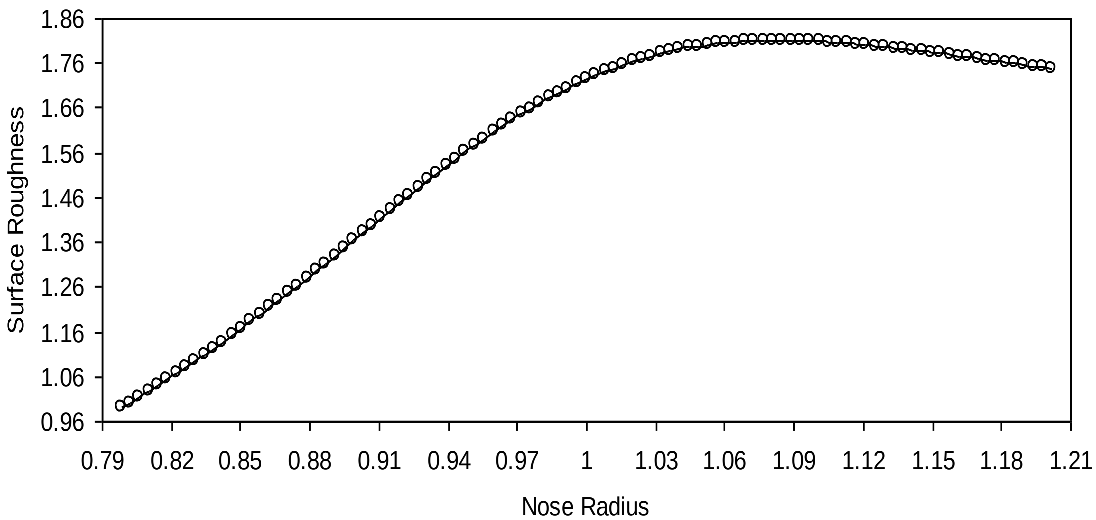

Figure 9. Surface roughness vs. nose radius (mm).

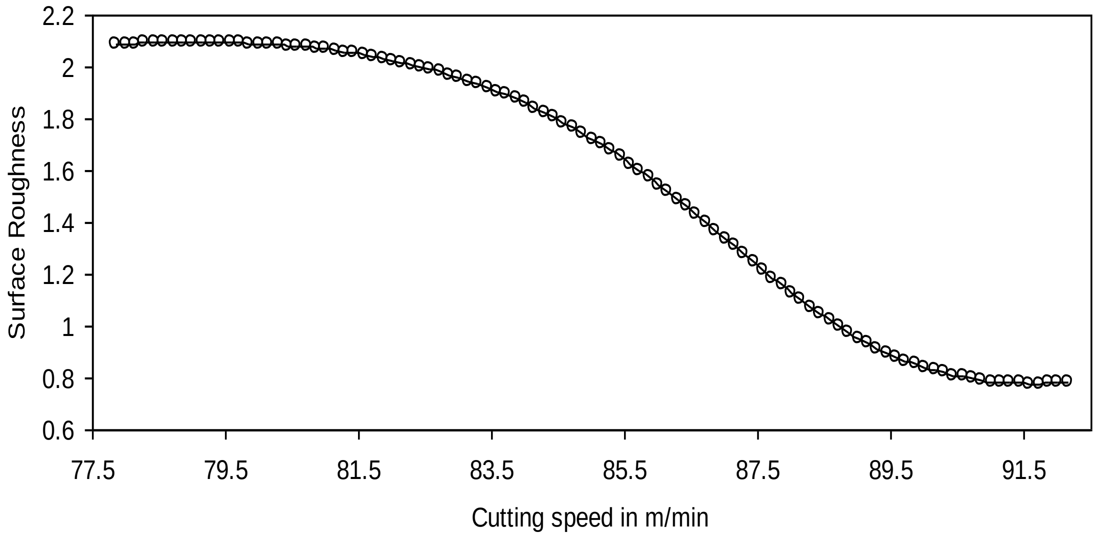

Figure 10. Surface roughness vs, cutting speed (m/min).

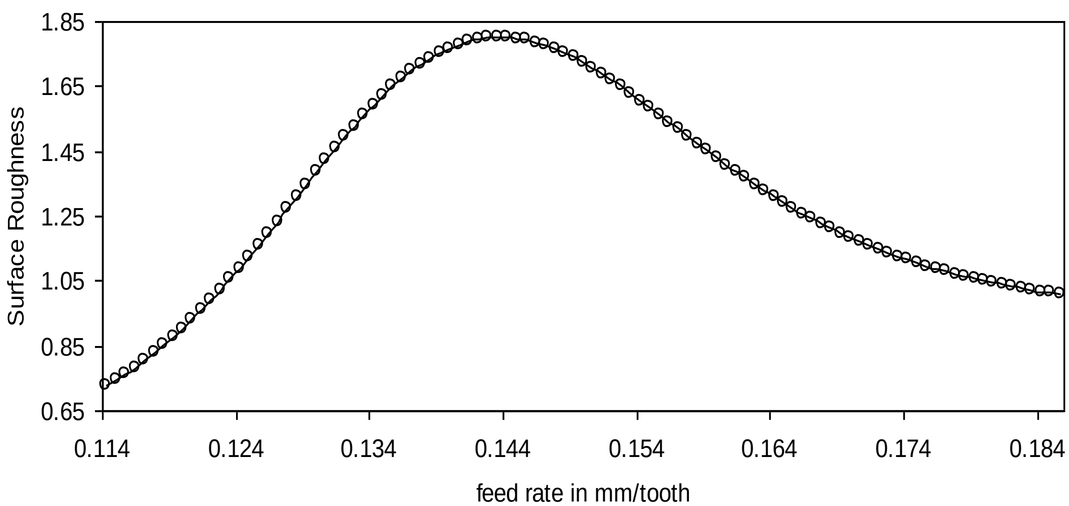

Figure 11. Surface roughness vs. cutting feed (mm/tooth)

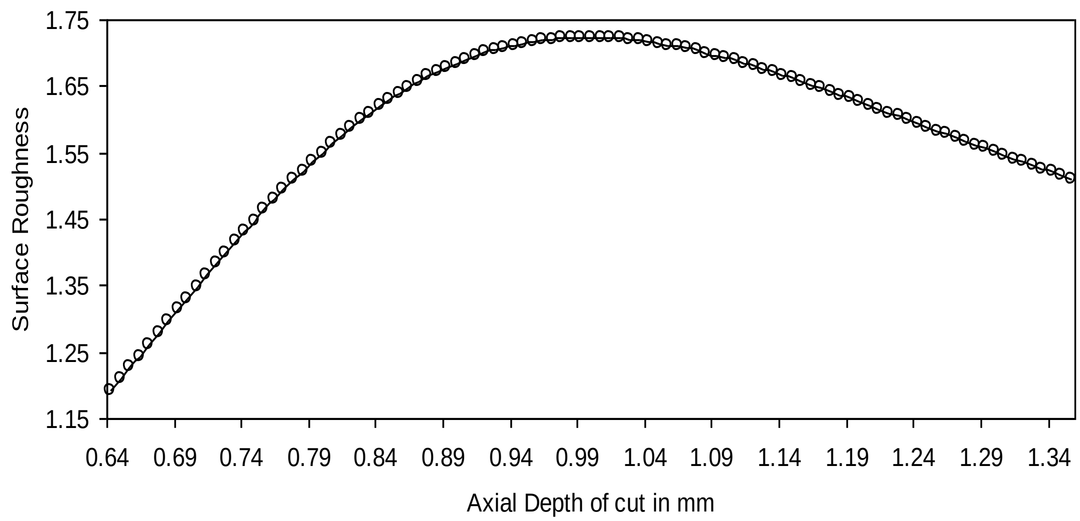

Figure 12. Surface roughness vs. axial depth of cut (mm).

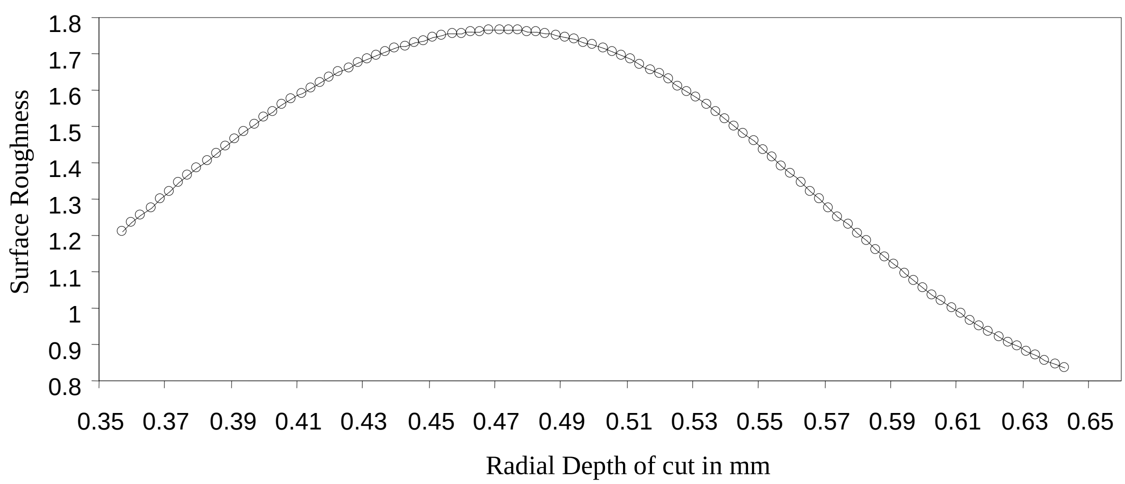

Figure 13. Surface roughness vs. radial depth of cut (mm)