Surface Roughness Prediction in High Speed Turning of Ti-6Al-4V: A Comparison of Techniques

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Abstract. Surface finish of machined products is important and plays an important role in ascertaining its quality and other attributes. Surface roughness of difficult to machine materials like titanium alloys are difficult to model due to several factors influencing it. This study makes an attempt to compare the performance of a statistical technique, Response Surface Methodology (RSM) and two Artificial Neural Network (ANN) techniques namely Multi Layered Perceptron (MLP) and Radial Basis Function Neural Network (RBFNN) to model and predict the surface roughness parameters $R_a$ and $R_t$ in high speed turning of Ti-6Al-4V. Experiments have been carried out using uncoated carbide inserts under dry condition. The input parameters for the modeling studies include cutting speed, feed rate and depth of cut. This work also makes use of tool wear and cutting tool vibration ($V_y$) which are uncontrollable parameters as the inputs for modeling studies. The ANOVA analysis has revealed that feed rate and cutting tool vibrations are the most significant parameters affecting $R_t$ and cutting speed and vibrations affect $R_a$. A comparison between the modeling techniques revealed that RBFNN performed better in terms of prediction accuracy when compared to MLP and RSM.

1. Introduction

Titanium and its alloys are widely used in the production of parts and components for Biomedical, Aerospace, Automobiles and various other fields of engineering. Machining titanium is a complicated task as commented by Siekman in 1955, which is true and hence many researchers are still trying to study its poor machinability. In the current scenario, high speed machining (HSM) is gaining more importance to achieve higher productivity and lesser machining time, which defines the speeds higher than conventional machining [1]. Ti-6Al-4V is a grade 5 alloy which is considered as a difficult to cut material due to its lower thermal conductivity, high chemical reactivity and low modulus of elasticity [2]. As this alloy is highly corrosion resistant, it is a widely used and studied among other titanium alloys [3, 4].

Surface roughness is an important parameter in a machining process that has gained lot of attention in recent years [5]. Extensive experimental research studies on surface roughness of Ti-6Al-4V have been done by several researchers. Ginting et al. focused on dry machining of grade 5 alloys and its surface integrity and results revealed that uncoated carbide tools are preferable for finish or semi finish operations [6]. Sharma et al. studied the machining characteristics of titanium alloy experimentally and concluded that surface roughness fluctuates more with respect to variation in feed rate [7]. Various parameters can affect the quality of surface roughness and include machining parameters, application of coolant, material properties and uncontrollable parameters like tool wear, cutting forces and tool vibration [8].
Surface roughness is a complex entity, and to carry out modeling studies and understanding the relationship between the several interacting parameters is difficult. Surface roughness modeling and prediction can been done by several techniques like RSM, ANN and ANFIS, out of which ANN is the most promising technique. Tsvoveloudis, in his study used RSM and Adaptive Neuro Fuzzy Inference System (ANFIS) for predicting surface roughness in turning Ti-6Al-4V [9]. Salgado et al. carried out the prediction of surface roughness correlating cutting vibrations and surface roughness in dry turning. [10]. Some researchers have made an attempt to study the effect of tool vibrations on surface roughness using RSM. Hessainia et al. developed quadratic models of RSM for predicting cutting tool vibrations separately [11]. Upadhyay et al. focussed on the prediction of surface roughness in machining Ti-6Al-4V, using cutting parameters and tool vibrations [12].

Ozel nd Karpat focussed on the prediction of tool wear and surface roughness in turning AISI H-13 steel and AISI 52100 steel using regression and ANN and results showed that cutting force inputs and a single output neural network model achieved better results [13]. Upadhyay et al. compared ANN and RSM while modeling cutting forces in turning Ti-6Al-4V and ANN produced superior results [14]. Rao and Murthy used RSM, ANN and Support Vector Machine (SVM) to model and optimize cutting tool vibrations and surface roughness during machining steel. ANN and SVM outperformed RSM model in predicting surface roughness [15].

Pai et al. applied RBFNN for the assessment of flank wear in face milling of En-8. Two networks were developed with centers selected randomly and centers selected through batch fuzzy c means and its performance were compared with resource allocation network (RAN). The results revealed that RBFNN with centers selected through batch fuzzy c means produced superior results when compared with other two networks [16]. Sonar et al. applied RBFNN for prediction of surface roughness in turning. Results from this study revealed that its performance was slightly poor when compared to MLP [17].

From the literature survey carried out, it can be summarised that there has been less efforts in using RBFNN for modeling and prediction of surface roughness in HSM of titanium based alloys. The use of Conditional Fuzzy C Means (CFCM) algorithm in designing RBFNN and its use in machining modeling applications is very limited. Use of tool flank wear and cutting tool vibrations, which are considered as uncontrollable parameters, have been rarely used in modeling studies. This study investigates RSM, a widely used statistical modeling technique, MLP a widely used ANN technique and RBFNN, to model and predict the values of surface roughness parameters $R_a$ and $R_s$ in high speed turning of Ti-6Al-4V. Cutting parameters namely (i) cutting speed, (ii) feed rate, (iii) depth of cut, (iv) tool flank wear and (v) cutting tool vibrations have been considered as input parameters and surface roughness parameters $R_a$ (Arithmetic average roughness) and $R_s$ (Maximum peak to valley height) have been modelled separately as output parameters. 289 experimental data have been considered to train and test the individual models. Finally a comparison has been made between the three techniques based on their prediction accuracies.

### 2. Experimental setup and details

The work material used is Ti-6Al-4V round bars of 50 mm diameter and 200 mm length with chemical composition as mentioned in [18]. The experimental setup of this study is shown in figure 1. The experiments were conducted on a High Speed CNC turning centre, HMT Stallion 100SU under dry cutting conditions, using uncoated carbide inserts 883 consisting of MR4 chip breaker manufactured by SECO tools. Three level full factorial design has been used to design the experiments and was designed using MINITAB 17 statistical software [19]. 27 experiments were conducted and 289 experimental data were generated out of which 85% of the data was considered as training data and remaining 15% as test data.

The tool flank wear ($V_B^{max}$) developed on the insert was measured using Mitutoyo Tool Makers’ microscope. The tool flank wear was measured after each pass. Length of machining pass was 48 mm. Experiments were conducted till the limiting value of flank wear of 0.4 mm was reached [20].

The cutting vibrations produced during machining were measured online using Model 65-10 Isotron triaxial accelerometer (Meggitt make). The accelerometer sensed signals in three directions, i. e. x (depth of cut), y (cutting speed), z (feed) and were sent to a DNA-PPCx,
Power DNA cube (UEI make), at a sampling frequency of 10 kHz. The cutting vibrations along cutting speed ($V_y$) direction are found to be more sensitive to the different machining phenomenon, when compared to other two directions. Hence it has been considered for modeling studies.

The surface roughness measurement has been done offline using Taylor Hobson Taly Surf 50, a stylus type instrument. $R_a$ and $R_t$ have been measured after each machining pass considering 2.5 mm sampling length.

3. Response Surface Methodology
RSM is a mathematical and statistical tool used to model and analyse the problem, in which a response variable is influenced by independent variables and the main outcome is to optimize the response. The connection between preferred response and input variables is represented by the following equation:

$$y = \phi(v, f, d, VB_{\text{max}}, V_y)$$

(1)

where $y$ is the preferred response, in this work it is either $R_a$ or $R_t$ and $\phi$ is a response function, $v$ is cutting speed (m/min), $f$ is the feed rate (mm/rev), $d$ is depth of cut, $VB_{\text{max}}$ is the tool flank wear and $V_y$ is the cutting tool vibration in cutting speed direction.

The response variable can be modelled by considering a linear function and a quadratic function which are represented in Eq. (2) and (3) respectively.

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k + \epsilon$$

(2)

$$y = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \beta_{ii} x_i^2 + \sum_{i<j} \beta_{ij} x_i x_j + \epsilon$$

(3)

where $\epsilon$ is represented as the error observed in the response $y$, $\beta_i$, $\beta_{ii}$ and $\beta_{ij}$ ’s are the regression coefficients [21]. $x_i$ are the coded variables that correspond to the different input parameters.

4. Artificial Neural Network
Neural network are the web of neurons interconnected just like in a human brain which produce electrical signals of different pattern. It is designed in such a way to perform tasks, similar to a human brain. A network is constructed by the interconnection of 'neurons' or 'processing units', and the processing ability can be improved by tuning the interunit connection strengths or weights thereby reducing the error between the actual and predicted values [22]. In this study, two types of neural network techniques have been used namely Multi Layered Perceptron Neural Network, which is a widely used feed forward neural network and Radial Basis function Neural Network using Conditional Fuzzy C Means (CFCM) clustering algorithm for evolving the centers of the RBF units.
4.1. Multi Layered Perceptron (MLP)

MLP is a widely used supervised feed forward neural network. It contains three layers namely input, hidden and an output layer. These layers are interconnected in such a way that each individual neuron in a layer is interconnected to all the neurons in the next layer. The network consists of weights and biases which are present in between the input layer, hidden layer and between hidden and output layer, so that the network can perform its function by varying these [23].

The output of a neuron is given by

\[ N = \sum_{i=1}^{p} w_i x_i + b \]  

(4)

where \( p \) is the number of inputs, \( w_i \) is the interconnecting weights, \( x_i \) is the input and \( b \) is the bias for the neuron. The weights are varied by a method in connection with the network layers to achieve the expected output which is called training a network [24]. The supervised network involves a method which provides the network with a series of sample inputs and outputs. Then the output from the network is matched with the expected output and error is calculated. The error between the predicted and experimental output is minimised by varying the weights and biases of the network. The target is to reduce the mean of these errors which is represented in eq. (5).

\[ \text{Error} = \frac{1}{Q \sum_{k=1}^{Q} (t(k) - a(k))^2} \]  

(5)

where \( t(k) \) is the actual output, \( a(k) \) is the predicted output and \( Q \) is the number of epochs. In this study, back propagation algorithm has been used and the details are available in [25].

The network performance is evaluated by using mean square error (MSE). The MSE is calculated as

\[ \text{MSE} = \frac{(\text{Actual output} - \text{Network output})^2}{2} \]  

(6)

The MLP using the standard Back Propagation algorithm has been implemented using MATLAB R2014b [26].

In this study, 5 inputs namely cutting speed, feed rate, depth of cut, \( \text{VB}_{\text{max}} \) and \( V_y \) have been considered as inputs. Surface roughness parameters \( R_a \) and \( R_t \) have been considered as the individual outputs. Figure 2(a) and 2(b) show the corresponding two MLPNN models.

The number of hidden neurons has been varied from 5 to 30 in steps of 5 neurons, to find the optimum number of neurons which results in best prediction performance. The goal has been set to
0.001 (e), number of epochs and momentum rate (α) has been set to 1000 and 0.003 respectively and the learning rate (η) has been varied between 0.025 and 0.1 to achieve the least MSE and highest prediction accuracy. The momentum rate has been fixed to 0.003 after several trials.

4.2. Radial Basis Function Neural Network (RBFNN)
Radial basis functions were first introduced to solve real multi-variable interpolation problems. A radial basis function is a feed forward network which consists of three layers. An input layer which is made up of sensory units, a hidden layer which applies a non-linear transformation from input space to the hidden space consisting of neurons with radial basis activation functions and an output layer which supplies the output of the network to the activation patterns applied to the input layer [24]. Each node of the hidden layer consists of a center μ_i and a width σ_j. Gaussian transfer functions are used in the hidden layer of neurons which is given in Eq. (7).

\[ \varphi_i(\mu) = -\exp\left(\frac{|x-\mu_i|^2}{2\sigma_j^2}\right) \]

(7)

where x is an input vector, μ_i is the center of the RBF unit and σ_j is a spread factor or width of the unit [27]. In an RBF network, if there are K radial basis units in the intermediate layer and one output layer, then the output is represented as in Eq. (8).

\[ y = \sum_{i=1}^{K} w_i \varphi_i(||x-\mu_i||^2) + w_0 \]

(8)

where x and μ_i are as defined as in Eq. (7), φ represents the activation function of the radial basis units, w_i represents the weights by which output of a radial unit is multiplied in the output layer and w_0 is a constant [28]. The smoothness property of the activation function is controlled by the width. The weights connecting the hidden and output units are established by the gradient descent method as the output is a non-linear function of the inputs. RBF models are simple and easy to implement.

4.2.1 Conditional Fuzzy c-means algorithm (CFCM) The RBFNN makes use of Conditional Fuzzy C-Means algorithm for fixing the number of units and the center location in the RBF units. Clustering algorithms have been often used as a pre-processing phase in the design of radial basis function (RBF) neural networks to build a link between the independent and response variables. It is essential to consider the labelling data on the output patterns. The output data has been used to create some meaningful groups in the input space. W. Pedrycz introduced Conditional Fuzzy C-Means (CFCM), a clustering method which reveals a structure in the patterns [29]. It makes use of interpolation as the method of disclosing the structure in the input space conditioned based upon some linguistic landmarks defined in the output space [30, 31].

The details of CFCM clustering algorithm used to create the centers of the RBF units are available in [30].

The CFCM algorithm creates the centers, which has been used to train the RBFNN. In order to create the centers, same input parameters have been considered. Ra and Rt are the two output parameters. The training of CFCM has been carried out with different number of centers and the target error has been set to 0.001.

4.2.2 Width of RBF units Spread factor or width of the RBF unit is a parameter which controls the refinement properties of the interpolating function. The width can be kept constant for all the RBF units [31]. In this study, the widths have been kept constant and are selected by trial and error to minimise the MSE and maximise prediction accuracy obtained.

4.3 Normalization of data
The experimental data in this study have been normalized before using in both the neural network models and actual data without normalization has been used for RSM modeling.
5. Results and Discussion

5.1 Response Surface Methodology

RSM quadratic models have been developed for $R_a$ and $R_t$. Three levels of cutting speed (150, 175, 200) m/min, feed rate (0.15, 0.2, 0.25) mm/rev and depth of cut (0.8, 1, 1.2) mm have been considered.

Models have been developed using 246 (85%) experimental data and remaining 43 (15%) for testing the developed model. The multiple regression equations for $R_a$ and $R_t$ are given in Eq. (9) and (10) respectively. These models have been developed using the full quadratic backward elimination method and alpha has been set to 0.05. These equations contain linear, square and interaction terms. The coefficient of regression ($R^2$) for $R_a$ has been found to be 0.7536 whereas for $R_t$, it has been found to be 0.6977. From these developed equations, the prediction of surface roughness ($R_a$ and $R_t$) have been carried out for test data.

$$R_a = 0.85 + 0.00577 \, \text{Speed} + 14.57 \, \text{Feed} - 6.33 \, \text{DOC} + 10.84 \, \text{Tool wear} + 0.00370 \, \text{Vy}$$
$$+ 1.625 \, \text{DOC} \times \text{DOC} + 0.000041 \, \text{V}_y \times \text{V}_y - 0.0603 \, \text{Speed} \times \text{Feed} + 0.01086 \, \text{Speed} \times \text{DOC}$$
$$- 0.04179 \, \text{Speed} \times \text{Tool wear} + 7.03 \, \text{Feed} \times \text{DOC} - 17.77 \, \text{Feed} \times \text{Tool wear} - 0.0413 \, \text{Feed} \times \text{Vy}$$  \hspace{1cm} (9)

$$R_t = 12.15 + 0.0138 \, \text{Speed} + 41.2 \, \text{Feed} - 34.25 \, \text{DOC} + 37.21 \, \text{Tool wear} - 0.02305 \, \text{Vy}$$
$$+ 11.48 \, \text{DOC} \times \text{DOC} + 0.000284 \, \text{V}_y \times \text{V}_y - 0.2221 \, \text{Speed} \times \text{Feed} + 0.0403 \, \text{Speed} \times \text{DOC}$$
$$- 0.1053 \, \text{Speed} \times \text{Tool wear} + 29.65 \, \text{Feed} \times \text{DOC} - 57.4 \, \text{Feed} \times \text{Tool wear} - 7.37 \, \text{DOC} \times \text{Tool wear}$$  \hspace{1cm} (10)

The ANOVA results for reduced quadratic models for $R_a$ and $R_t$ are shown in Tables 1 and 2. From Table 1, it can be seen that cutting speed, feed rate, depth of cut and $V_y$ are significant variables affecting $R_a$, as the $p$ values are less than 0.05, but tool wear has a $p$ value of 0.781, hence it has been found to be statistically insignificant. F value reveals that cutting speed is the most significant parameter affecting $R_a$ followed by feed. It is also evident from the table that, all other square and interaction terms are having $p$ values less than 0.05, including those containing tool wear, which is not significant individually. Table 2 shows the ANOVA results for reduced quadratic model for $R_t$. It can be seen that depth of cut and tool wear have $p$ values greater than 0.05, hence they have been found to be insignificant. The two important parameters which have a significant effect on $R_t$ are feed rate and $V_y$ which is evident from the F values. A similar observation as before can be made with regard to square and interaction terms, with all of them being significant.

| Source       | DF | Adj SS  | Adj MS  | F-Value | P-Value |
|--------------|----|---------|---------|---------|---------|
| Model        | 13 | 20.4209 | 1.57084 | 54.59   | 0.000   |
| Linear       | 5  | 4.3176  | 0.86351 | 30.01   | 0.000   |
| Speed        | 1  | 3.1224  | 3.12245 | 108.51  | 0.000   |
| Feed         | 1  | 0.2814  | 0.28144 | 9.78    | 0.002   |
| DOC          | 1  | 0.2700  | 0.26998 | 9.38    | 0.002   |
| Tool wear    | 1  | 0.0022  | 0.00222 | 0.08    | 0.781   |
| $V_y$        | 1  | 0.4529  | 0.45292 | 15.74   | 0.000   |
| Square       | 2  | 0.3898  | 0.19489 | 6.77    | 0.001   |
| DOC*DOC      | 1  | 0.1654  | 0.16536 | 5.75    | 0.017   |
| $V_y$*$V_y$  | 1  | 0.2261  | 0.22611 | 7.86    | 0.005   |
| 2-Way Interaction | 6 | 5.7526  | 0.95876 | 33.32   | 0.000   |
| Speed*Feed   | 1  | 0.5286  | 0.52857 | 18.37   | 0.000   |
| Speed*DOC    | 1  | 0.2707  | 0.27072 | 9.41    | 0.002   |
| Speed*Tool wear | 1 | 1.6592  | 1.65924 | 57.66   | 0.000   |
| Feed*DOC     | 1  | 0.5029  | 0.50288 | 17.48   | 0.000   |
| Feed*Tool wear | 1 | 1.1248  | 1.12485 | 39.09   | 0.000   |
| Feed*$V_y$   | 1  | 0.2615  | 0.26146 | 9.09    | 0.003   |
| Error        | 232| 6.6759  | 0.02878 |         |         |
| Total        | 245| 27.0968 |         |         |         |
Table 2: ANOVA table for reduced quadratic model – R_t

| Source                  | DF | Adj SS   | Adj MS   | F-Value | P-Value | P-Value |
|-------------------------|----|----------|----------|---------|---------|---------|
| Model                   | 13 | 266.662  | 20.5125  | 41.19   | 0.000   |         |
| Linear                  | 5  | 141.264  | 28.2567  | 56.75   | 0.000   |         |
| Speed                   | 1  | 23.959   | 23.9588  | 48.12   | 0.000   |         |
| Feed                    | 1  | 58.636   | 58.6359  | 117.76  | 0.000   |         |
| DOC                     | 1  | 0.701    | 0.7011   | 1.41    | 0.237   |         |
| Tool wear               | 1  | 0.012    | 0.0119   | 0.02    | 0.877   |         |
| Vy                      | 1  | 51.944   | 51.9443  | 104.32  | 0.000   |         |
| Square                  | 2  | 20.359   | 10.1793  | 20.44   | 0.000   |         |
| DOC*DOC                 | 1  | 8.332    | 8.3320   | 16.73   | 0.000   |         |
| Vy*Vy                   | 1  | 11.517   | 11.5170  | 23.13   | 0.000   |         |
| 2-Way Interaction       | 6  | 53.383   | 8.8971   | 17.87   | 0.000   |         |
| Speed*Feed              | 1  | 7.377    | 7.3770   | 14.81   | 0.000   |         |
| Speed*DOC               | 1  | 3.466    | 3.4658   | 6.96    | 0.009   |         |
| Speed*Tool wear         | 1  | 10.709   | 10.7092  | 21.51   | 0.000   |         |
| Feed*DOC                | 1  | 8.919    | 8.9189   | 17.91   | 0.000   |         |
| Feed*Tool wear          | 1  | 11.590   | 11.5900  | 23.28   | 0.000   |         |
| DOC*Tool wear           | 1  | 2.982    | 2.9815   | 5.99    | 0.015   |         |
| Error                   | 232| 115.524  | 0.4979   | 0.001   |         |         |
| Total                   | 245| 382.186  |          |         |         |         |

A MSE of 0.05 has been used to calculate the prediction accuracies. Any error value above 0.05 between the predicted and experimental values has been considered as a misclassification. The same criterion has been used for calculating prediction accuracies in ANN models. The prediction accuracy for R_a is 93.08% for training data and 79.06% for test data, but for R_t, prediction accuracy has been found to be very low with a prediction accuracy of 33.04% for training and 20.93% for test data. R_t has been found to be highly sensitive to variation in cutting tool vibrations in speed direction (V_y). Also there is unusual variation in R_t with V_y [23]. Hence the prediction accuracy of R_t is lower, considering cutting vibrations as the input parameter. ANOVA has also established that R_t is more influenced by V_y and feed than other parameters.

5.2. Multi Layered Perceptron

Many trials have been performed during training of the MLP by changing the values of learning rate, momentum rate and number of hidden neurons in order to get highest prediction accuracy and lowest mean squared error.

| No. of hidden neurons | 5  | 10 | 15 | 20 | 25 | 30 |
|-----------------------|----|----|----|----|----|----|
| Accuracy on training data (%) | 99.5935 | 100 | 100 | 99.9998 | 99.9998 | 99.9998 |
| Accuracy on test data (%)  | 97.6742 | 97.6742 | 97.6742 | 99.1870 | 98.3740 | 98.3740 |
| MSE                    | 0.007340 | 0.007652 | 0.008355 | 0.00921 | 0.01 | 0.0105 |

Table 4: Results of testing of MLP (R_t)

| No. of hidden neurons | 5  | 10 | 15 | 20 | 25 | 30 |
|-----------------------|----|----|----|----|----|----|
| Accuracy on training data (%) | 100 | 99.5935 | 99.5935 | 99.5935 | 99.5935 | 99.5935 |
| Accuracy on test data (%)  | 97.6742 | 97.6742 | 97.6742 | 97.6742 | 97.6742 | 97.6742 |
| MSE                    | 0.00461 | 0.005174 | 0.00570 | 0.006174 | 0.006585 | 0.007015 |

MLP network produced the best result in terms of prediction accuracy of 100% for training data and 97.6742% for test data and the MSE has been found to be 0.007652 for 1000 epochs which is shown in Table 3. Table 4 shows the best possible results for R_t. It can be seen that for \( \eta = 0.025, \alpha = 0.003 \) with 5 hidden neurons, the network produced the best result with a prediction accuracy of 100% for training data and 97.6742% for test data with a least MSE of 0.00461.
5.3. RBFNN

The simulation parameters namely learning rate at 0.85 and momentum term at 0.05 have been maintained constant throughout the study. The RBFNN is trained using the centers of RBF units selected by CFCM clustering algorithm and varying the width values. The hidden and output units are connected by weights which have been established with the gradient descent approach. The epochs have been set to 1000. The width of the RBF units is determined using trial and error and is kept constant for all the RBF units. The results obtained from RBFNN for $Ra$ is shown in table 5. It can be seen that the highest prediction accuracy of 100% for both training and test data has been achieved with an MSE of 0.00951 for 32 RBF units with a width of 0.16.

Table 5: Results of testing of RBFNN ($Ra$) with different width for 32 RBF units

| Width | Accuracy on training data (%) | Accuracy on test data (%) | Average MSE |
|-------|-------------------------------|---------------------------|-------------|
| 0.12  | 99.5935                       | 97.6744                   | 0.010697    |
| 0.14  | 100                           | 100                       | 0.00885     |
| 0.16  | 100                           | 100                       | 0.00951     |
| 0.18  | 100                           | 99.1870                   | 0.01418     |
| 0.2   | 90.2439                       | 83.7209                   | 0.04176     |

It is clear from Table 5, as the width increased till 0.16, the MSE decreased and prediction accuracies increased. But with further increase in width, the performance of the network decreased and MSE increased.

The results obtained from RBFNN for $R_t$ is shown in table 6. It can be seen that the best possible result for $R_t$ has been obtained for 21 RBF units with a width of 0.18 achieving a prediction accuracy of 100% for both training and test data with an MSE of 0.00825.

Table 6: Results of testing of RBFNN ($R_t$) with different width for 21 RBF units

| Width | Accuracy on training data (%) | Accuracy on test data (%) | MSE     |
|-------|-------------------------------|---------------------------|---------|
| 0.12  | 99.5935                       | 97.6744                   | 0.00954 |
| 0.14  | 100                           | 100                       | 0.008817|
| 0.16  | 100                           | 100                       | 0.008419|
| 0.18  | 100                           | 100                       | 0.00825 |
| 0.2   | 97.1545                       | 95.3488                   | 0.0242  |

Figure 3 shows the comparison of $Ra$ and $R_t$ for both experimental and RBFNN predicted values for test data. The plots have been developed based on the results for best possible simulation parameters, as given in Tables 5 and 6. It can be seen that the predicted values of $Ra$ are not very close to the experimental values, with mismatch for some data. For $R_t$, there is a positive correlation between the experimental and predicted values.

Figure 3: Comparison of experimental and RBF predicted values (test data) (a) $Ra$ and (b) $R_t$

5.4. Comparison of Techniques

Table 7 shows the comparative evaluation of Response Surface Methodology, Multi Layered Perceptron Neural Network and Radial Basis Function Neural Network for the prediction of surface roughness parameters $Ra$ and $R_t$ in high speed turning of Ti-6Al-4V. It can be seen that RBFNN produces the highest prediction accuracy, when compared to RSM and MLPNN. RBFNN produced a
prediction accuracy of 100% for both $R_a$ and $R_t$ for both training and test data. The network has been able to classify 100% unseen patterns using conditional fuzzy c means clustering algorithm. The use of CFCM provides an effective method for establishing the number and location of centers of the RBF units, which improves the performance of RBFNN. This clustering algorithm brings in supervised characteristic, by using the information from the outputs. MLPNN produced prediction accuracy which has been found to be better than RSM. MLP generates a more compact ANN model, when compared to RBFNN. The prediction accuracies produced using RSM have been found to be very low. ANN has the ability to capture any degree of non-linearity that exists between the output and input data and exhibits good generalisation over RSM [32]. This comparison shows the ability of neural networks to predict surface roughness parameters $R_a$ and $R_t$ more accurately than RSM.

### Table 7: Comparative evaluation of the performance of RSM, MLPNN and RBFNN

| Technique /Network | Accuracy ($R_a$) (%) | MSE | No. of hidden neurons/RBF unit | Accuracy ($R_t$) (%) | MSE | No. of hidden neurons/RBF unit |
|-------------------|----------------------|-----|-------------------------------|----------------------|-----|-------------------------------|
|                   | Training data | Test data | | Training data | Test data | |
| RSM               | 93.08     | 79.06     | 0.013579         | -                    | 33.04     | 20.93     | 0.234806         | -                    |
| MLPNN             | 100       | 97.6742   | 0.007652         | 10                   | 100       | 97.6742   | 0.00461          | 5                    |
| RBFNN             | 100       | 100       | 0.00951          | 32                   | 100       | 100       | 0.00825          | 21                   |

6. Conclusion
In this study, investigations have been made to compare the performance of three modeling and prediction techniques namely Response Surface Methodology, Multi Layered Perceptron Neural Network and Radial Basis Function Neural Network by considering cutting speed, feed rate, depth of cut, tool wear and cutting tool vibrations ($V_y$) in high speed turning of Ti-6Al-4V for predicting the surface roughness parameters $R_a$ and $R_t$. The following conclusions can be drawn from this study:

1. Cutting speed is a highly significant parameter, which affects surface roughness parameters $R_a$, followed by feed whereas for $R_t$, feed rate and cutting tool vibrations have been found to be significant which is revealed from ANOVA.
2. RSM, a widely used statistical technique gives poor prediction accuracies for both $R_a$ and $R_t$.
3. MLP, a widely used supervised ANN model gives good prediction accuracies, which is intermediate between RSM and RBFNN. It generates a compact ANN model with only 10 and 5 hidden neurons for $R_a$ and $R_t$ respectively.
4. Conditional Fuzzy C-Means clustering algorithm is very effective in identifying optimal location of centers in the RBF units, which improves the performance of RBFNN.
5. RBFNN gives the best possible performance of 100% prediction accuracies for both training and test data for $R_a$ and $R_t$. This establishes its effectiveness in modeling and predicting surface roughness parameters in high speed turning of Ti-6Al-4V.

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