Comparison of multiple regression and radial basis artificial neural network models in turning of mild steel components

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Abstract: In the present work, an attempt is made to develop the numerical models to predict the Material removal Rate (MRR) in a turning process of mild steel specimens using the computational methods namely Multiple regression Analysis MRA and Radial Basis Artificial Neural Network. The machining parameters dealt were Spindle speed, Feed rate and depth of cut. The experiments were conducted in accordance with the Taguchi’s L16 orthogonal array on a conventional lathe using single point HSS Tool. The results as predicted by the computational methods were compared with the experimental results and it was found that a Radial Basis ANN model performed better in comparison with MRA.

Keywords: Artificial neural networks, Taguchi technique, DOE, MRA, Material removal rate (MRR)

Nomenclature

| Symbol | Description |
|--------|-------------|
| F      | Feed rate (mm/rev) |
| DOC    | Depth of cut (mm) |
| N      | Spindle Speed (rpm) |
| MRR    | Material Removal Rate (m³/min) |

1. INTRODUCTION

Mild steel is used as the material in the manufacturing of various components used in Aircraft, ship building and automobile industries. The turning of Mild steel specimens are dealt in this work, by considering the MRR as a machining performance characteristic and Spindle speed, Feed rate and depth of cut as the turning process parameters. It is essential to build the numerical models which can predict machining performance beforehand. In this regard extensive work has been carried out by various researchers. Francisco et al developed a mathematical model for cutting force that uses multiple quadratic regression model as a base. Experiments were conducted based on full factorial design by considering Depth of cut, cutting speed and feed rate as the machining parameters and Ti-N coated cutting tool. Regression coefficients of 0.99 and 0.98 were obtained for Radial cutting force and feed force respectively [1]. Anuja et al built neural network-based prediction model for the estimation of surface roughness in hard turning of AISI H 13 steel. It was observed that a 3-7-7-1 ANN architecture yielded a minimum Root mean square error. ANN predicted values were found to be in a fair match with the experimental results [2]. A Genetic algorithm (GA) assisted ANN model was used to predict the surface roughness and it was found that a drastic increase in the prediction accuracy was achieved. Optimization techniques namely GA and Particle swarm optimization (PSO) were used to arrive at the optimal cutting parameters for the minimization of cutting forces and surface roughness and
maximization of tool life [3]. Natarajan et al. predicted the values of surface roughness using ANN in turning of Brass C2600 using CNC machine. The predicted values of surface roughness were successfully compared to those of experimental data [4]. The mathematical formulae for tool vibration, surface roughness, cutting time and power consumption was developed using Multiple Regression analysis for the turning of medium carbon steel by using tungsten carbide tools [5]. Das Gupta et al employed a technique of MRA to develop the mathematical model to estimate the tool life. It was found that feed rate has a greater influence on the tool life tool life. It was found that feed rate has a greater influence on the tool life compared to spindle speed and Depth of cut [6]. Selvam et al utilized regression analysis to develop the prediction model to estimate the surface roughness in turning of medium carbon steel (hardened C45). The experiments were conducted according to Taguchi's orthogonal array (L9). Further the optimum machining conditions of surface roughness were found out using genetic algorithm [7]. Multiple Regression Analysis technique was utilized to das utilized to develop the mathematical model for power consumption, cutting force and surface roughness. Further by employing Particle Swarm Optimization, a multi-objective optimization was carried out [8]. Grey relation based multi-objective optimization was carried out for a better finish in the turning operation of mono crystalline Germanium work piece. Rotational speed, Depth of cut, feed rate, tool overhang and rake angle were considered as the process parameters. The machining characteristics namely waviness error, profile error and surface roughness were considered in the turning process [9]. Hamezh et al utilized PSO for the optimization of machining process parameters (Depth of cut, feed rate and spindle speed) in ball end milling of Carbon Fiber reinforced epoxy composites. The machining process parameters dealt in their work were Surface roughness, Material removal rate and Machining forces. Response surface methodology was employed to formulate the objective function required for PSO. It was observed that the software results were in close match with the experimental values [10]. RSM based empirical model was used to predict the surface roughness in the turning operation of Stainless steel. It was observed that the feed rate and cutting speed influences the surface roughness the most and least respectively [11]. ANN was successfully applied to predict the chatter that commonly occurs during the turning operation. Accuracy of prediction was found to be greater than 90% [12]. Ferreira et al used ANOVA to find the impact of quality of tool, feed rate and cutting speed in the quality of the surface during the turning operation of AISI H13. Experiments were conducted based on Design of Experiments. The results show that cutting speed does not influence the surface integrity [13].

From the literature review, it is clear that a Radial Basis ANN was not utilized to build the prediction model in the turning process of Mild steel specimens. Also, no such studies were made which involves the comparison of the prediction performance of MRA and Radial basis ANN models for the turning operation of Mild steel material. Having motivated by this, a work is taken where the MRA and Radial basis ANN computational models were developed. Further the prediction performance of both the models were compared in the present work.

2. EXPERIMENTAL DETAILS

2.1 Specimen details
The turning operation of Mild steel specimen, as shown in figure 1, is conducted on a conventional lathe machine using HSS tool brazed with tungsten carbide tip. The mild steel specimens used in this work were of diameter 50mm and length 125 mm.
2.2 Experimental Plan

Experiments were conducted in accordance with the Design of Experiments (Taguchi's L27 orthogonal array) for a 3-Level input design. The turning process variables used in this work are Spindle speed, Feed rate and Depth of cut. The details of the 3-Level input design is given in Table 1.

| Levels | Feed (mm/rev) | Speed (rpm) | Depth of cut (mm) |
|--------|---------------|-------------|-----------------|
| 1      | 0.051         | 90          | 0.2             |
| 2      | 0.059         | 315         | 0.4             |
| 3      | 0.065         | 500         | 0.6             |

Experiments are conducted as per according to Taguchi's L27 array and the design matrix is as given in Table 2. Material removal rate (MRR) is used as a machining Performance indicator in this study and is calculated as per equation 1.

\[
MRR = \frac{(Initial\ Volume - Final\ Volume)}{Machining\ Time}
\]  

Table 2. Taguchi's L27 orthogonal Array

| S. No | Feed (mm/rev) | Depth of cut (mm) | Speed (rpm) | Experimental MRR (m³/min) |
|-------|---------------|------------------|-------------|--------------------------|
| 1     | 0.051         | 0.2              | 90          | 3.09E-07                 |
| 2     | 0.051         | 0.2              | 315         | 1.28E-06                 |
| 3     | 0.051         | 0.2              | 500         | 1.73E-06                 |
| 4     | 0.051         | 0.4              | 90          | 1.54E-07                 |
| 5     | 0.051         | 0.4              | 315         | 6.38E-07                 |
| 6     | 0.051         | 0.4              | 500         | 8.68E-07                 |
| 7     | 0.051         | 0.6              | 90          | 2.30E-07                 |
| 8     | 0.051         | 0.6              | 315         | 9.33E-07                 |
| 9     | 0.051         | 0.6              | 500         | 1.26E-06                 |
| 10    | 0.059         | 0.2              | 90          | 3.61E-07                 |
| 11    | 0.059         | 0.2              | 315         | 1.41E-06                 |
| 12    | 0.059         | 0.2              | 500         | 2.12E-06                 |
| 13    | 0.059         | 0.4              | 90          | 1.76E-07                 |
| 14    | 0.059         | 0.4              | 315         | 6.94E-07                 |
| 15    | 0.059         | 0.4              | 500         | 9.19E-07                 |
| 16    | 0.059         | 0.6              | 90          | 2.89E-07                 |
| 17    | 0.059         | 0.6              | 315         | 1.04E-06                 |

Figure 1 Mild steel Specimen
3. MULTIPLE REGRESSION ANALYSIS

Multiple Regression Analysis technique is used to develop a Mathematical EQUATION TO predict the Material removal Rate. The experimental Data collected in accordance with Taguchi’s L27 orthogonal array is used to perform Multiple Regression Analysis. The objective function for the Material Removal Rate is formulated for the three independent variables speed (N), feed rate (F) and Depth of Cut (DOC) using Minitab 17 statistical software. The general form of the MRA equation is as per equation 2 [14]. Using the experimental data in equation 2, the empirical formula for MRR is constructed and is as given in Equation 3

\[ y = \beta_0 + \beta_1 x_1 + \cdots + \beta_n x_n + \varepsilon \]  
(2)

\[ y = \text{output parameter}, x = \text{input parameter}, \varepsilon = \text{Error} \]

By using the experimental history from Table 3 a regression equation is developed in Minitab software.

\[ \text{MRR} = 0.000006 \times F + 0.000001 \times \text{DOC} - 0.000015 \times F \times \text{DOC} \]  
(3)

Where, \( F \) is Feed rate (mm/rev), \( N \) = Spindle speed (rpm) and \( \text{DOC} \) = Depth of cut (mm)

The predictions for the test cases are done as per equation 3 and are given in Table 3. In Table 3, the comparison of both the experimental and numerical results are also made.

| S. No | Feed (mm/rev) | Depth of cut (mm) | Speed (rpm) | Experimental MRR (m³/min) | MRR Predicted (m³/min) | Error % |
|-------|---------------|------------------|-------------|--------------------------|------------------------|---------|
| 18    | 0.059         | 0.6              | 500         | 1.42E-06                 |                        |         |
| 19    | 0.065         | 0.2              | 90          | 3.63E-07                 |                        |         |
| 20    | 0.065         | 0.2              | 315         | 1.50E-06                 |                        |         |
| 21    | 0.065         | 0.2              | 500         | 2.17E-06                 |                        |         |
| 22    | 0.065         | 0.4              | 90          | 1.80E-07                 |                        |         |
| 23    | 0.065         | 0.4              | 315         | 7.56E-07                 |                        |         |
| 24    | 0.065         | 0.4              | 500         | 1.00E-06                 |                        |         |
| 25    | 0.065         | 0.6              | 90          | 2.73E-07                 |                        |         |
| 26    | 0.065         | 0.6              | 315         | 1.11E-06                 |                        |         |
| 27    | 0.065         | 0.6              | 500         | 1.50E-06                 |                        |         |

4. RADIAL BASIS ANN

Artificial neural networks are similar to our brain which comprises of neurons that are distributed in input, hidden and output layers. The number of neurons in the input layer depends upon the number of independent variables and the number of neurons in the output layer depends upon the dependent variables. Radial basis function network is a type of Artificial neural network, in which activation function is radial basis. It is based on a conventional approximation theory and has a capability of universal approximation. Because of its faster computational capability and simpler structure, it may
be used. It is based on a conventional approximation theory and has a capability of universal approximation. Because of its faster computational capability and simpler structure, it may be used instead of Multilayer perceptron network. A typical three-layer Radial basis ANN structure is as shown in figure 2. Every node in the hidden layer uses a Radial Basis function, which is a non linear activation function.

![Figure 2. A typical Radial basis neural network [14]](image)

In a Radial basis neural network used in the present work, the number neurons in the input layer are 3, representing Spindle speed, Feed rate and Depth of cut. There are 27 neurons in the hidden layer and 1 neuron in the output layer represents Material Removal Rate. To develop the Radial basis ANN, MATLAB software is used. For the radial basis ANN a spread factor of 0.53 is used. A total of 27 training cases were used and are as given in Table 2. The prediction results and accuracy of Radial Basis ANN for the test cases are tabulated in Table 4.

Table 4. Prediction results of Radial basis ANN for the test cases

| Feed (mm/rev) | Depth of cut (mm) | Speed (rpm) | MRR Experimental (m³/min) | MRR ANN (m³/min) | ANN Error |
|---------------|------------------|-------------|--------------------------|------------------|-----------|
| 0.051         | 0.4              | 224         | 3.84e-07                 | 4.094e-07        | 6.62%     |
| 0.062         | 0.5              | 224         | 5.39e-07                 | 5.572e-07        | 3.33%     |
| 0.065         | 0.5              | 140         | 4.48e-07                 | 4.1039e-07       | -8.39%    |

5. RESULTS AND DISCUSSIONS

The turning of Mild steel composites were done on a conventional lathe by considering process parameters as spindle speed, feed and depth of cut. The process performance characteristic dealt in this work is Material Removal Rate. Using the experimental results a MRA model and a Radial Basis ANN were built and the results for the test cases are as given in Table 3 and Table 4. The prediction errors of MRR in a MRA model for the three test cases are 23.8%, 24.4% and 9.1% respectively. The prediction errors in a Radial Basis ANN model are 6.62%, 3.33% and -8.39% for the three test cases. A radial Basis ANN outperformed a MRA model in the prediction of MRR by 17.18%, 21.07% and 0.71% respectively. In Table 5, the prediction error of 27 training cases for the MRA model is compared with that of Radial basis ANN model.
Table 5. Prediction results of MRA and Radial basis ANN for the 27 Training cases

| S No | Prediction error of MRA model | Prediction error of Radial basis model |
|------|-------------------------------|--------------------------------------|
| 1    | -14.2395                      | 2.38188E-07                         |
| 2    | 72.4219                       | -5E-09                              |
| 3    | 79.5954                       | 2.95954E-08                         |
| 4    | -160.2472                     | -6.2459E-07                        |
| 5    | 37.3041                       | -2.5078E-08                         |
| 6    | 53.9171                       | 7.74193E-08                         |
| 7    | -94.3478                      | 2.64348E-07                         |
| 8    | 52.0900                       | -3.4298E-08                         |
| 9    | 64.5238                       | -1.7778E-08                         |
| 10   | -4.4321                       | -2.3934E-07                         |
| 11   | 73.2624                       | -2.2695E-09                         |
| 12   | 82.2170                       | 2.86792E-08                         |
| 13   | -127.4019                     | -2.7288E-07                         |
| 14   | 42.3631                       | 4.14986E-08                         |
| 15   | 56.4744                       | 6.26766E-08                         |
| 16   | -46.3668                      | 1.99308E-07                         |
| 17   | 59.2093                       | 4.93732E-08                         |
| 18   | 70.2113                       | -6.7606E-08                         |
| 19   | -8.8454                       | 1.41086E-07                         |
| 20   | 73.5821                       | 2.99625E-08                         |
| 21   | 81.7972                       | 0                                   |
| 22   | -122.2222                     | -4.4444E-07                         |
| 23   | 47.0899                       | -2.963E-08                          |
| 24   | 60.0000                       | -2.88E-08                           |
| 25   | -48.3516                      | 1.64102E-07                         |
| 26   | 63.5135                       | -3.7477E-08                         |
| 27   | 73.0000                       | -2.1333E-08                         |

6. CONCLUSION

In this work, the turning of GFRP composite specimens are carried out on a conventional lathe with use of HSS tool and considering feed rate, spindle speed and depth of cut as the machining parameters. Using the 3-Level input experiments are conducted as per Taguchi's L16 Array and the prediction models of MRR were developed using MRA and Radial Basis ANN. It was found that predictions as done by Radial Basis ANN were found to be much better than a MRA model. Thus, a Radial Basis ANN is much suitable for the prediction of MRR in turning of GFRP composites.

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