ANN BASED PREDICTION OF SURFACE ROUGHNESS IN TURNING

A. Hemantha Kumar¹, Krishnaiah.G.² V.Diwakar Reddy³

¹Assoc.Prof. Annamacharya Institute of Technology and Sciences, Rajampet.
ahkaits@gmail.com

²Professor, Department of Mechanical Engineering, S.V.U. College of Engg.,
S.V. University, Tirupathi.

³Associate Prof., S.V.U College of Engineering, S.V.University, Tirupati

ABSTRACT

Surface roughness, an indicator of surface quality is one of the most specified customer requirements in a machining process. For efficient use of machine tools, optimum cutting parameters (speed, feed and depth of cut) are required. Therefore it is necessary to find a suitable optimization method which can find optimum values of cutting parameters for minimizing surface roughness. The turning process parameter optimization is highly constrained and nonlinear. In present work, machining process was carried out on Mild steel material in dry cutting condition in a lathe machine and surface roughness was measured using Surface Roughness Tester. To predict the surface roughness, an artificial neural network (ANN) model was designed through back propagation network for the data obtained. Comparison of the experimental data and ANN results show that there is no significant difference and ANN was used confidently. The results obtained, conclude that ANN is reliable and accurate for solving the cutting parameter optimization.

Key words
Turning process, non-ferrous material, surface roughness, artificial neural network (ANN), and optimization

1. INTRODUCTION

Now-a-days, due to the increasing demand of higher precision components for its functional aspect, surface roughness of a machined part plays an important role in the modern manufacturing process. Turning is a machining operation, which is carried out on lathe. 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. To achieve the desired surface finish, a good predictive model is required for stable machining. Generally, these models have a complex relationship between surface roughness and operational parameters, work materials and chip breaker types.

Artificial neural networks (ANNs) are information processing systems, and since their inception, they have been used in several areas of engineering applications. In experimental studies, some of the operating conditions of a system can be investigated. For this type of experimental work, experts and special equipment are needed. It also requires too much time and high cost. ANNs have been trained to solve non-linear and complex problems that are not exactly modeled mathematically. ANNs eliminate the limitations of the classical approaches by extracting the desired information using the input data. Applying ANN to a system needs sufficient input and output data instead of a mathematical equation. Furthermore, it can continuously re-train for new data during the operation, thus it can adapt to changes in the system. ANNs can also be used to deal with problems with incomplete and imprecise data. In this work, artificial neural network model have been developed to predict the surface roughness on the machining mild steel metal. To judge the efficiency and ability of the model to predict surface roughness values, percentage deviation and average percentage deviation are used. The results obtained, conclude that ANN is reliable and accurate for predicting the values. The actual Ra value was obtained as 1.961µm and the corresponding predicted surface roughness value was 1.9021µm, which implies greater accuracy.

2. LITERATURE SURVEY

Since turning is the primary operation in most of the production processes in the industry, surface finish of turned components has greater influence on the quality of the product. Surface finish in turning had been found to be influenced in varying amounts by a number of factors such as feed rate, work material characteristics, work hardness, unstable built-up edge, cutting speed, depth of cut, cutting time, tool nose radius. According to these parameters, a detailed literature survey is carried out as follows. Srikanth and Kamala [1] proposed a real coded genetic algorithm (RCGA) to find optimum cutting Parameters and explained various issues of RCGA and its advantages over the existing approach of binary coded genetic algorithm (BCGA). Franic and Joze [2] used binary coded genetic algorithm (BCGA) for the optimization of cutting parameters. This genetic algorithm optimizes the cutting conditions having an influence on production cost, time and quality of the final product. Suresh et al. [3] developed optimum surface roughness predictive model using binary coded genetic algorithm (BCGA). This GA program gives minimum and maximum values of surface roughness and their respective optimal machining conditions. Yang and Tarng [4] used Taguchi
method for design optimization on surface quality. An orthogonal array, the signal-to-noise (S/N) ratio and the analysis of variance (ANOVA) were employed to investigate the cutting characteristics. Avishek et al. [5](2009) conducted a study of feasibility of online monitoring of surface roughness in turning operations using a developed optoelectrical transducer. Regression and neural network (NN) models were exploited to predict surface roughness and compared to actual and on-line measurements. Sakir et al. [6] worked on the prediction of surface roughness using artificial neural network in lathe and investigated the effect of tool geometry on surface roughness in universal lathe and carried out machining process on mild steel in dry cutting condition using various insert geometry at depth of cut of 0.5 mm.

Optimization of machining parameters not only increases the utility for machining economics, but also the product quality to a great extent. The dynamic nature and widespread usage of turning operations in practice have raised a need for seeking a systematic approach that can help to set-up turning operations in a timely manner and also to achieve the desired surface roughness quality. After a detailed literature survey, it is inferred that there are no appropriate surface recognition models for machining mild steel metal in lathe turning. The experimental works were conducted in a leading pump manufacturing company. The seamless pipe which is being manufactured in the pump industry made up of mild steel requires more surface finish in the inner.

3. EXPERIMENTAL PROCEDURES AND CONDITIONS

The concept of dry applications may be considered as a rigorous solution in achieving reduced improved surface finish while maintaining cutting forces or power at reasonable levels, if the dry lubrication system can be properly designed. Dry lubrication technique not only provides reduction in tool wear or increase in tool life and improvement in surface roughness but also reduces the consumption of cutting fluid. The machining tests have been carried out by straight turning of medium carbon steel(mild steel) on a lathe by a standard HSS uncoated and carbide insert with ISO designation-SNMG 120408 at different speed-feed and depth combinations. Machining has been considered to be an effective dry application because it offers positive part on environment friendliness as well as techno-economical benefit. The conditions under which the machining tests have been carried out are briefly given below. All these parameters have been selected as per tool manufacturer’s recommendation as well as industrial practices for machining medium carbon steel(mild steel) with HSS.

Table 1. Examples of Training Cutting conditions of HSS on medium carbon steel

<table>
<thead>
<tr>
<th>Speed (rpm)</th>
<th>Feed (mm/rev)</th>
<th>Depth of cut (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>228</td>
<td>0.05</td>
<td>0.04</td>
</tr>
<tr>
<td>450</td>
<td>0.08</td>
<td>0.6</td>
</tr>
<tr>
<td>740</td>
<td>0.1</td>
<td>1.0</td>
</tr>
</tbody>
</table>

L27 -Model
3.1 Proposed ANN model for Surface Roughness

We have developed an ANN model to determine surface roughness in a dry environment. The capability of the ANN model is to generalize unseen data dependent on several factors. These factors are appropriate selection of input-output parameters, the distribution of the input-output dataset, and the format of the presentation of the dataset to the neural network. Selected input parameters are the significant variables that affect the surface roughness while perform turning operation under dry environment. As input parameters, we consider cutting speed, feed rate, depth of cut. The output parameter of the model is the surface roughness. Details of the input/output parameters of the proposed ANN model are illustrated in Figure 4.

![Schematic diagram of ANN for Ra.](image)

**Figure 1** Schematic diagram of ANN for Ra.

3.2 Collection of Input-Output Dataset

The machining tests have been carried out by straight turning of medium carbon steel on a lathe by a standard uncoated carbide insert with ISO designation-SNMG 120408 at different cutting speeds (V), feed rates (f), depth of cuts (d) under dry condition. During machining trials, the cutting insert was withdrawn at regular intervals to examine the pattern and extent of wear under a metallurgical microscope. After each trial, the average surface roughness value was also measured by a mitutoyo SJ-201P. Thus several pairs of output variables in response to the different combinations of machining/input parameters have been obtained.

3.3 Pre-processing of Input-Output Dataset

The capability of the artificial neural network (ANN) model to generalize regarding unseen data dependent on several factors such as appropriate selection of input-output parameters of the system, the distribution of the input-output dataset, the format of the presentation of the input-output dataset to the neural network. For our ANN model, the input parameters used are the three main machining parameters (cutting speed, feed rate, depth of cut), while the output dataset are the one process parameters (average surface roughness).

\[
P_i = \begin{bmatrix} \text{CuttingSpeed}, V \\ \text{FeedRate}, f \\ \text{Depthofcut}, d \end{bmatrix} \quad T_i = [\text{Avg.SurfaceRoughness}, Ra]
\]
In this study, several machining tests were carried out and thus 36 pairs of input-output dataset were obtained during the machining trials. Before training the ANN by feeding the dataset to the network and the input-output mapping, one significant task is to process the experimental data into patterns. Training and testing pattern vectors are formed before input-output dataset are fed to network. Each pattern is formed with an input condition vector (Pi) and the corresponding target vector (Ti), which is shown in the matrix. Before training the network, the input-output dataset were normalized within the range of -1 to +1 using the MATLAB command ‘premnmx’.

3.4 Neural Network Design and Training

The network architecture/ topology or features such as number of neurons and layers are very important factors that determine the functionality and generalization capability of the network. Training of an ANN plays a significant role in designing the direct ANN-based prediction.

The number of neurons in the hidden layer is intentionally chosen to start with 20 neuron and hidden neurons are added to the hidden layer incrementally. The addition of hidden neurons continues until there is no significant progress in network performance. The performance of the network was evaluated by mean squared error (MSE) between the experimental and the predicted values for every output nodes in respect of training the network. The feedback from that processing is called the “average error” or “performance”. Once the average error is below the required goal or reaches the required goal, the neural network stops training and is, therefore, ready to be verified. ANN Training performance is shown in the Figure – [2]. The input-output dataset consisting of 36 patterns was divided randomly into two categories: training dataset consist of 75% of the data and test dataset which consist 25% the data. There are 27 training patterns considered for ANN modeling surface roughness. After the training, the weights are frozen and the model is tested for validation. In this work, the network is validated in terms of agreement with experimental results.

The momentum constant and learning rate used in this model is 0.5 and 0.1 respectively. The maximum number of training epochs that was set is 10,000 and the training error goal was 0.0001. After the training is completed, the actual weight values are stored in a separate file. The value of $R^2$ and MAPE values between the network predictions and the
experimental values using training and test dataset for different network architecture have been shown in Table 1 and 2.

**3.5 Performance Evaluation of the Designed Network**

Training and testing performance of the optimum network architecture can be evaluated. After post processing the network predicted values by using the MATLAB command ‘postmnmx’, regression analysis was adopted to find the coefficient of determination value ($R^2$) for both training and testing phases to judge performance of each network. Another index termed as mean absolute percentage of error (MAPE) is also used in this analysis to judge the training and testing performance. The coefficient of determination ($R^2$) and mean absolute percentage of error (MAPE) values for different network architecture have been presented in Table 3. For clarity not all of the hidden neurons that were considered during designing and developing the ANNs model are shown in Table 3.

It is shown from the Table 3 that network with 1 hidden layer and 25 neurons in the hidden layer with ‘tansigmoid’ and ‘purelin’ transfer function in the hidden and output layer respectively and trained with Levenberg-Marquardt algorithm provides the best result. It can also been seen from Table 3 that increasing the number of neurons from 25 to 30 has no significant improvement on the performance of the network. So, 3-25-1 network architecture was selected as the optimum ANN model.

Table 3 $R^2$ values between Network Prediction and Experimental values

<table>
<thead>
<tr>
<th>Hidden Layer</th>
<th>20</th>
<th>25</th>
<th>30</th>
<th>20</th>
<th>25</th>
<th>30</th>
</tr>
</thead>
<tbody>
<tr>
<td>Regression</td>
<td>0.998</td>
<td>0.999</td>
<td>0.998</td>
<td>0.873</td>
<td>0.91</td>
<td>0.86</td>
</tr>
</tbody>
</table>

**4. RESULTS AND DISCUSSIONS**

In this study, an artificial neural network (ANN) with feed-forward back-propagation algorithm was trained and the training epoch (cycles) set for each network is 10,000. The purpose of the training is to minimize the mean squared error (MSE. From Figure – (2) it
is seen that the network error goal is met at 119 epochs for the proposed ANN model, consists of 25 hidden neurons.

To find the best network, different training algorithms were tested. Transfer functions in the hidden and output layer and weight and bias learning function have also been changed and tested during design phase of the network. Finally, tangent of sigmoid function (‘tansigmoid’) and purely linear function (‘purelin’) were used as the transfer function in the hidden and output layer respectively. Training of the network was performed using Levenberg-Marquardt (LM) feed forward back propagation algorithm. The weight or bias learning algorithm used here is ‘learngdm’ that is gradient decent with momentum. The numbers of neurons in the hidden layer were found by trial and error method and finally 25 hidden neurons were chosen for the suggested network. The proposed network can be represented as 3-25-1.

To find the optimal network architecture, coefficient of determination ($R^2$) and mean absolute percentage of error (MAPE) between the network prediction and experimental values were calculated for every network for both training and testing phases. The coefficient of determination ($R^2$) represents the percent of data that is closest to the line of best fit. The value of $R^2$ varies between 0 to 1. If correlation coefficient, $R=0.91$ then $R^2=0.821$, which means that 82% of the total variation in network prediction can be explained by the linear relationship between experimental values and network predicted values. The other 18% of the total variation in network prediction remains unexplained. The coefficient of determination ($R^2$) and mean absolute percentage of error (MAPE) for different network topography have been shown in Table 3. From Table 3, it is shown that the value of $R^2$ increases up to hidden neuron 25. Then it starts to decrease mainly in terms of testing cases. The network architecture consisting of 1 hidden layer and 25 hidden neurons shows best values of $R^2$ for both training and testing stages of the network. So, the network consisting of 25 hidden neurons was selected as the optimum one in this research work. The summary of the proposed network architecture has been presented in Table 4. As, the input and output vectors were supplied to the network, it was a supervised learning scheme. The back-propagation learning algorithm with LM versions was used at the training stage of the network. Gradient decent learning rule is used in this study. The learning rate and momentum constant used here are 0.1 and 0.5 respectively.
Table 2 Examples of Test Cutting conditions of HSS on medium carbon steel at different hidden neurons

<table>
<thead>
<tr>
<th>S.No</th>
<th>Speed (rpm)</th>
<th>Feed (mm/r ev)</th>
<th>Depth of cut (mm)</th>
<th>Measured Surf. Roughness Ra (µm)</th>
<th>ANN Computed roughness Ra (µm) w.r.t hidden neurons</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>@20 Neurons Deviation (%)</td>
</tr>
<tr>
<td>1</td>
<td>250</td>
<td>0.06</td>
<td>0.5</td>
<td>1.96</td>
<td>1.902</td>
</tr>
<tr>
<td>2</td>
<td>250</td>
<td>0.06</td>
<td>0.7</td>
<td>2.10</td>
<td>2.162</td>
</tr>
<tr>
<td>3</td>
<td>250</td>
<td>0.06</td>
<td>0.9</td>
<td>2.07</td>
<td>1.795</td>
</tr>
<tr>
<td>4</td>
<td>360</td>
<td>0.07</td>
<td>0.5</td>
<td>1.84</td>
<td>2.013</td>
</tr>
<tr>
<td>5</td>
<td>360</td>
<td>0.07</td>
<td>0.7</td>
<td>1.98</td>
<td>2.179</td>
</tr>
<tr>
<td>6</td>
<td>360</td>
<td>0.07</td>
<td>0.9</td>
<td>2.09</td>
<td>2.354</td>
</tr>
<tr>
<td>7</td>
<td>540</td>
<td>0.09</td>
<td>0.5</td>
<td>2.04</td>
<td>1.513</td>
</tr>
<tr>
<td>8</td>
<td>540</td>
<td>0.09</td>
<td>0.7</td>
<td>2.10</td>
<td>2.083</td>
</tr>
<tr>
<td>9</td>
<td>540</td>
<td>0.09</td>
<td>0.9</td>
<td>2.28</td>
<td>2.124</td>
</tr>
<tr>
<td></td>
<td>Average</td>
<td></td>
<td></td>
<td></td>
<td>18.58</td>
</tr>
</tbody>
</table>

5. CONCLUSIONS

One of the primary objectives in machining operation is to produce product with low cost and high quality. The objective of this work was to develop an ANN model to predict surface roughness while turning medium carbon steel under dry environment. An ANN model has been developed for prediction of surface roughness as a function of cutting parameters. The model has been proved to be successful in terms of agreement with experimental results. The proposed model can be used in optimization of cutting process for efficient and economic production by forecasting the surface roughness in turning operations. The multilayer feed forward network consisting of three inputs, 25 hidden neurons (tangent sigmoid neurons) and one outputs (network architecture represented as 3-25-1) was found to be the optimum network for the model developed in this study. The back propagation learning algorithm has been used in the developed feed forward single hidden layer network. A good performance of the neural network has been achieved with coefficient of determination (R²) between the model prediction and experimental values are 0.873, 0.910, and 0.861 and in terms hidden neurons 20, 25, 30 respectively of Ra. The MAPE values for those variables are 18.58, 9.78, 13.48 in terms hidden neurons 20, 25, 30 respectively.
7. REFERENCES


