# Chapter 15
# A Comparative Analysis of Surface Roughness Prediction Models Using Soft Computing Techniques

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**Abstract** Surface roughness is one of the significant index to measure the product quality of the machined parts. The objective of this work is to contribute towards the development of prediction models for surface roughness. In this work, the predictive models were developed for turning operations using soft computing techniques; support vector regression (SVR) and artificial neural network (ANN). The turning experiments are conducted to obtain the experimental data. The developed predictive models were compared using relative error and validated using hypothesis testing. The results indicate that both techniques provide a close relation between the predicted values and the experimental values for surface roughness and are appropriate to predict the surface roughness with significant acceptable accuracy. It is found that ANN performs better as compared to SVR.

**Keywords** Surface roughness · Artificial neural network · Support vector regression

## 15.1 Introduction

Predictive modelling is widely used in machining operations to improve the product quality, minimize the production cost and lower the power consumption. Surface roughness is one of the common index to measure the product quality of the machined parts (Sarikaya and Güllü 2014). Surface roughness of machined parts improves the fatigue strength, successive machining benefits, tribological characteristics, quality of fit in two mating parts and corrosive resistance etc. (Kant and Sangwan 2014). Literature depicted that surface roughness is one of the primary performance evaluation criterion in machining operations followed by machining cost and material removal rate (Yusup et al. 2012). The surface roughness of the machined parts depends upon various factors such as cutting parameters, properties of the work piece, cutting tool

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K. S. Sangwan and C. Herrmann (eds.), *Enhancing Future Skills and Entrepreneurship*, Sustainable Production, Life Cycle Engineering and Management,
https://doi.org/10.1007/978-3-030-44248-4_15

type and their geometry etc. The theoretical models available in the text books are unable to incorporate the dynamic behavior of the machining operations and failed to predict the surface roughness precisely (Davim et al. 2008). The researchers have used various modelling techniques to overcome the dynamic behavior of machining operations (Garg et al. 2016; Sangwan et al. 2015; Beatrice et al. 2014; Kant and Sangwan 2015a, b, c; Kant et al. 2013; Sangwan and Kant 2017; Pawanr and Garg 2019; Pal and Chakraborty 2005; Aykut Arapo˘glu and Mehmet Alper Sofuo˘glu 2017). Therefore, it is essential to accumulate and analyze the real time experimental data related to surface roughness and control parameters to develop a precise predictive model. In the present study, predictive model for the product quality in terms of surface roughness has been developed using support vector regression (SVR) and artificial neural network (ANN) during turning of mild steel 1045. Sandvik made carbide inserts were used as cutting inserts in a dry cutting environment for the turning operation. The proposed models were compared on the basis of relative error and validated using hypothesis testing.

## 15.2 Experimental Work

The main objective of this work is to develop predictive models due to which only three machining parameters are considered to simplify the modelling procedure. The turning parameters including cutting speed ($v$), feed rate ($f$) and cutting depth ($d$) and their levels are shown in Table 15.1.

Experiments were conducted on a heavy-duty HMT Centre lathe machine tool having maximum 2300 rpm and 5.5 kW motor rating. Mild steel grade AISI 1045 was selected as a work piece material for the turning because it has wide range of industrial and commercial applications. The carbide cutting inserts of grade TNMG 16 04 04 were used for cutting with tool holder PTGNR 2020K16. The Taylor and Hobson make profilometer was used to acquire the surface roughness data from the work piece. The surface roughness readings were taken on three equally spaced locations and their mean was computed to obtain the average surface roughness. The detailed information of experimental setup, measurements and design of experiment can be seen in reference Kant and Sangwan (2014).

**Table 15.1** Machining parameters and their levels

| Factor/levels | I | II | III |
|---|---|---|---|
| $v$ (m/min) | 103.31 | 134.30 | 174.14 |
| $f$ (mm/revolution) | 0.12 | 0.16 | 0.2 |
| $d$ (mm) | 0.5 | 1.0 | 1.5 |

## 15.3 Development of Predictive Models for Turning

In this section, the obtained experimental data is used to develop the predictive models using SVR and ANN.

### *15.3.1 Support Vector Regression*

An online SVR toolbox for SVR modelling developed by Parrella (2007) in MATLAB is used for predicting the surface roughness. A combined vector of all the three input parameters (*v*, *f*, *d*) as a training set 'x' and the training set 'y' representing response parameter (surface roughness) is used. Twenty-seven sets of input-output pairs are used for training of the SVR model. The performance of the SVR model majorly depends upon the two variables known as insensitive loss function (ε) and cost function and are adjusted by the users to obtain the best outputs. Training parameters used for this study are $\varepsilon = 0.01$; $C = 1000$; kernel type = radial basis function (RBF); kernel parameter = 30. SVR checks the verification of Karush–Kuhn–Tucker (KKT) conditions and simultaneously trains the data one by one by adding each sample to the function. If the KKT conditions are not verified then the sample is stabilized using the stabilization technique, else the sample is added. To optimize the values, the stabilization technique dynamically changes the SVR parameters of insensitive loss function and cost function.

### *15.3.2 Artificial Neural Network*

After several trials, it was found that the parameters shown in Table 15.2 leads to accurate results in minimum time.

The network structure 3-7-1 means that it consists of three neurons in the input layer, seven neurons in the hidden layer and output layer with one neuron. 22 random values from the experimental data were chosen for training and five random values were used for testing the network based on selected 80%:20% ratio. A feed forward back propagation algorithm was used to train the network by assigning random

**Table 15.2** Selected ANN parameters for surface roughness prediction

| ANN parameters | Value |
|---|---|
| Structure of network | 3-7-1 |
| Training/testing data | 22/5 |
| Performance function | Mean Square Error |
| Network algorithm | Feed forward back propagation |
| Transfer function | Logsig, tansig |

**Table 15.3** The weights and biases between neurons of input and hidden layer

| Wjk, j = 3, k = 7 | W1k | W2k | W3k | Bias (bk) |
|---|---|---|---|---|
| 1 | 2.924 | 0.014 | 4.534 | −5.241 |
| 2 | 3.582 | 0.831 | −4.220 | −4.490 |
| 3 | −2.837 | 4.284 | 1.151 | 3.088 |
| 4 | 3.467 | −4.160 | 3.723 | −0.839 |
| 5 | −1.004 | 5.115 | 2.841 | 1.423 |
| 6 | −5.034 | 2.821 | 1.429 | −7.357 |
| 7 | −3.223 | −4.798 | 5.559 | −3.962 |

**Table 15.4** The weights and bias between neurons of hidden and output layer

| Wk, z k = 7, z = 1 | W1k |
|---|---|
| 1 | 0.755 |
| 2 | 0.291 |
| 3 | 0.566 |
| 4 | −0.346 |
| 5 | 0.643 |
| 6 | 1.633 |
| 7 | −0.656 |

weights and biases to interconnected neurons. This algorithm works on the principal of gradient decent method and updates the weights and biases in each iteration until the minimum mean square error is achieved between the target values and training values. The final weights and biases between the input layer and hidden layer are shown in Table 15.3. The weights between hidden layer and output layer are shown in Table 15.4. The bias value between hidden and output layer is 0.491. The neural network was trained using the parameters listed in Table 15.2 and it was observed that mean square error decreased until 250 iterations and after this point it was steady. The training was stopped after 250 iterations and the developed neural network was tested using the random experimental values, which were not used for training process.

## 15.4 Comparison and Validation of Predictive Models

Equation (15.1) is used to compute the relative errors between the predicted values by the proposed models and their respective experimental values of the surface roughness and are graphically presented in Fig. 15.1.

$$\text{Relative Error}\ (\%) = \frac{|\text{Predicted value - Experimental value}|}{\text{Experimental Value}} * 100 \qquad (15.1)$$

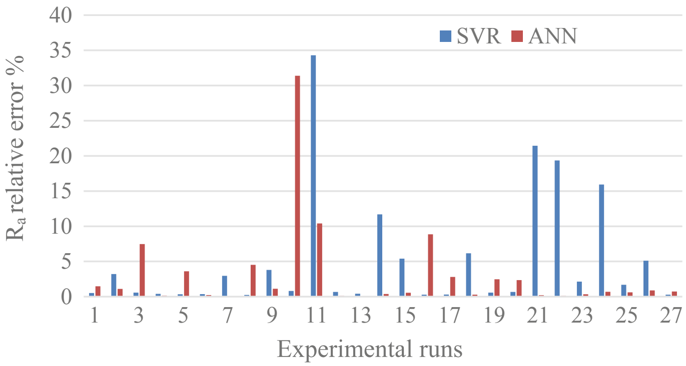


**Fig. 15.1** Comparison of prediction capabilities of ANN and SVR in terms of relative error %

The average relative errors of 5.17% and 3.07% were found by SVR and ANN respectively.

Mean relative error illustrates that the ANN performs better as compared to SVR. It shows that the well-trained network model can take an optimal performance and has greater accuracy in predicting surface roughness as compared to SVR. Both the techniques are suitable for predicting the surface roughness in an acceptable range. However, the model generation and training procedure of ANN took more time as compared to SVR. Also, both the techniques are appropriate to predict the surface roughness with significant acceptable accuracy. Goodness of fit was calculated and compared for both techniques using some representative hypothetical tests and are shown in Table 15.5. These tests are *t*-test to test the means, *f*-test and Levene's test for variance. In all these tests, the *p*-values found to be greater than 0.05, which means that the null hypothesis cannot be rejected. The *p*-values in Table 15.5 also indicate that there is no significant evidence to conclude that the experimental data and the data predicted by SVR and ANN models differ. Therefore, both predictive models have statistically satisfactory goodness of fit for the modelling point of view.

**Table 15.5** Results of Hypothesis testing to compare the models at 95% confidence level based on p-value

| Tests | p-value | |
|---|---|---|
| | SVR | ANN |
| Mean paired t-test | 0.840 | 0.882 |
| Variance F-test | 0.624 | 0.802 |
| Levene's test | 0.386 | 0.784 |

## 15.5 Conclusions

In this work, predictive models using soft computing techniques SVR and ANN were developed for surface roughness. SVR is capable of accurately predicting the surface roughness during turning operations. The mean relative error between the predicted and experimental values for the SVR model was found to be 5.17%. The predictive model developed using the ANN shows that the surface roughness values could be obtained with the selected ANN parameters. ANN has provided a close relation between the predicted values and the experimental values. The mean relative error for the predicted and experimental values using ANN was found to be 3.07%. It has been found that the model developed using ANN is capable of predicting accurately using a small number of training samples. The developed predictive models are compared using relative error and validated using hypothesis testing. It was found that ANN performs better as compared to SVR. The predictive capability could also be used for automatic monitoring. With the known boundaries of surface roughness and machining conditions, machining could be done with a relatively high rate of success leading to better surface finish.

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