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Modeling and prediction of surface roughness in turning operations using artificial neural network and multiple regression method

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ABSTRACT

Machine parts during their useful life are significantly influenced by surface roughness quality. The machining process is more complex, and therefore, it is very hard to develop a comprehensive model involving all cutting parameters. In this study, the surface roughness is measured during turning at different cutting parameters such as speed, feed, and depth of cut. Full factorial experimental design is implemented to increase the confidence limit and reliability of the experimental data. Artificial neural networks (ANN) and multiple regression approaches are used to model the surface roughness of AISI 1040 steel. Multiple regression and neural network-based models are compared using statistical methods. It is clearly seen that the proposed models are capable of prediction of the surface roughness. The ANN model estimates the surface roughness with high accuracy compared to the multiple regression model.

1. Introduction

Machined surface characteristics greatly affect the fatigue strength, corrosion resistance and tribological properties of machined components. The surface finish obtained after machining determines the quality of material. High surface roughness values reduce the fatigue life. Therefore, control of the machined surface is essential to safe turning operations (Sharma, Suresh, Rakesh, & Sharma, 2008). Machine parts that are in contact with other elements or materials during their useful life are influenced by surface quality and dimensional precision. Therefore, the most important aspects in manufacturing processes are measuring and characterizing of surface properties. The surface roughness is one of the important properties of workpiece quality in the turning process. A good surface roughness and hence poor surface roughness improve the tribological properties, fatigue strength, corrosion resistance, and esthetic appeal of the product. The various models for the optimum surface roughness have been reported in several research works. These models can be arranged as follows: the multiple regression technique, mathematical modeling based on the physics of the process, the fuzzy-set-based technique, and neural network modeling (Arbizu & Pérez, 2003; Kohli & Dixit, 2005; Risbood, Dixit, & Sahasrabudhe, 2003). The studies of some researchers on turning and milling are given below.

Thiele and Melkote (1999) carried out an experimental investigation of effects of workpiece hardness and tool edge geometry on surface roughness in finish hard turning using CBN tools. They applied an analysis of variance (ANOVA) to the experimental results in order to distinguish whether differences in surface quality for various runs were statistically important. Feng and Wang (2002) focus on developing an empirical model for the prediction of surface roughness using non linear regression analysis with logarithmic data transformation in finish turning. Also, they investigated the impact of workpiece hardness, feed, tool point angle, depth of cut, spindle speed, and cutting time on the surface roughness. Chou, Evans, and Barash (2002) studied the performance and wear behavior of different cubic boron nitride (CBN) tools in finish turning of hardened AISI 52100 steel. Tool performance was evaluated by taking into the part surface finish and the tool flank wear. Zuperl and Cus (2003) proposed a neural network-based approach to ensure simple, fast, and efficient optimization of all important turning parameters. They used the multi-objective optimization technique for cutting conditions taking into consideration the technological, economic, and organizational limitations. Özel and Karpat (2005) presented a neural network modeling to predict surface roughness and tool flank wear over the machining time for variety of cutting conditions in finish hard turning. They also developed the regression models in order to capture process-specific parameters by using the experimental data obtained from hardened AISI H-13 and AISI 52100 steels. Sharma et al. (2008) proposed a neural network modeling to estimate surface roughness in turning operations. Machining variables (i.e. cutting forces

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and surface roughness) are measured during turning at different cutting parameters such as approaching angle, speed, feed, and depth of cut. Ho, Tsai, Lin, and Chou (2009) used an adaptive network-based fuzzy inference system (ANFIS) with the genetic learning algorithm to predict the workpiece surface roughness in the end milling process. They applied the hybrid Taguchi-genetic learning algorithm (HTGLA) in the ANFIS to determine the most suitable membership functions. Zain, Haron, & Sharif, 2010 presented the ANN model for predicting the surface roughness in the end milling machining process. They recommended that the best combination of cutting conditions for achieving the best surface roughness value could be obtained at high speed with a low feed rate and radial rake angle.

The aim of present study is to develop an effective approach based on artificial neural networks and multiple regression to predict the surface roughness in AISI 1040 steel. For this purpose, full factorial experimental design is implemented to investigate the effect of the cutting parameters (i.e. cutting speed, feed rate, and depth of cut) on the surface roughness. The multiple regression models are tested by aiding the analysis of variance (ANOVA). Multilayer perception (MLP) architecture with back-propagation algorithm having two different variants is used in neural network. The performances of multiple regression and neural network-based models are compared by means of statistical methods. The proposed models can be used effectively to predict the surface roughness in turning process. The results obtained show that ANN produces the better results compared to multiple regression.

2. Material and methods

2.1. Modeling of surface roughness

In turning, there are many factors affecting the surface roughness such as tool variables, workpiece variables, and cutting conditions. Tool variables consist of tool material, nose radius, rake angle, cutting edge geometry, tool vibration, tool point angle, etc., while workpiece variables comprise material, hardness, and other mechanical properties. Furthermore, cutting conditions include speed, feed, and depth of cut. Since the hard turning process contains many parameters, it is complex and difficult to select the appropriate cutting conditions and tool geometry for achieving the required surface quality (Singh & Rao, 2007). Therefore, some scientific approaches are required to represent the process. It is clear that the proper model selection for the surface roughness is essential for the machining of hard materials.

The surface roughness average *Ra* is generally defined on the basis of the ISO 4287 norm, which is the arithmetical mean of the deviations of the roughness profile from the central line *lm* along the measurement. This definition is given in Eq. (1) (Arbizu & Pérez, 2003).

$$R_a = \frac{1}{L}\int_0^L |y(x)|dx \tag{1}$$

where L is the sampling length, and y is coordinate of the profile curve.

The relationship between the surface roughness and independent machining variables can be defined as:

$$R_a = C \cdot V^n \cdot f^m \cdot d^p \cdot r^l \cdot \varepsilon \tag{2}$$

where *Ra* is the surface roughness in μm; V, f, d, and r are the cutting speed (m/min), feed rate (mm/rev), depth of cut (mm), and tool nose radius (mm), respectively. $C, n, m, p,$ *and* l are constants and ε is random error. Eq. (1) can be given as shown in Eq. (3) in order to facilitate the presentation of the constants and parameters. The arithmetic average height *Ra* and maximum peak to valley height *Rt* of turned surfaces can be computed as follows:

$$R_a \approx \frac{f^2}{32 \cdot r} \tag{3}$$

$$R_t \approx \frac{f^2}{8 \cdot r} \tag{4}$$

where r = tool nose radius (mm) and f = feed rate (mm/rev). Eqs. (3) and (4) show that while surface roughness proportionally increases with the feed rate, a large tool nose radius reduces the surface roughness of a turned workpiece. The model does not consider any imperfections in the process such as tool vibration or chip adhesion (Sharma et al., 2008).

2.2. Multiple regression modeling for surface roughness

Multiple regression is a statistical technique that allows us to determine the correlation between a continuous dependent variable and two or more continuous or discrete independent variables. It can be used for a variety of purposes such as analyzing of experimental, ordinal, or categorical data. Thus, it can be considered to be helpful in predicting the surface roughness (Reddy, Padmanabhan, & Reddy, 2008). In order to predict the surface roughness, the second-order regression equation can be expressed as:

$$\begin{aligned} R_a = \beta_0 + \beta_1 \cdot V + \beta_2 \cdot f + \beta_3 \cdot a + \beta_4 \cdot V^2 + \beta_5 \cdot f^2 + \beta_6 \cdot a^2 \\ + \beta_7 \cdot V \cdot f + \beta_8 \cdot V \cdot a + \beta_9 \cdot f \cdot a \end{aligned} \tag{5}$$

Ra is the estimated surface roughness and V, f, and a are the cutting speed, feed rate, and depth of cut, respectively. The coefficients β_0, $\beta_1, \beta_2, \ldots, \beta_9$ are to be estimated using suitable methods. Thereafter, the analysis of variance (ANOVA) is used to seek the relationship between a response variable (output parameter) and two or more continuous or discrete independent variables. The performance criterions given in Eqs. (12) and (13) are applied to compare the developed models.

2.3. Surface roughness prediction strategy using artificial neural network

Artificial neural networks (ANNs) emulating the biological connections between neurons are known as soft computing techniques. ANNs can reproduce some functions of human behavior, which are formed by a finite number of layers with different computing elements called neurons. In order to construct a network, the neurons are interconnected. The organization of connections determines the type and objectives of the ANNs. The processing ability of the network is stored in the interunit connection strengths, or weights, which are tuned in the learning process. The training algorithm (or learning) is defined as a procedure that consists of adjusting the weights and biases of a network that minimize selected function of the error between the actual and desired outputs (Gareta, Romeo, & Gil, 2006; Kalogirou, 2003; Karatas, Sozen, & Dulek, 2009).

ANNs are widely used in many applications such as forecasting, control, data compression, pattern recognition, speech, vision, medicine, and power systems. Neural network models provide an alternative approach to analyze the data, because they can deduce patterns in the data. A simple process element of the ANN is shown in Fig. 1. The network has three layers; the input, hidden, and output layers. The input and output layers are defined as nodes, and the hidden layer provides a relation between the input and output layers. Initially, the weights of the nodes are random and the network has not any knowledge. For a given input pattern, the

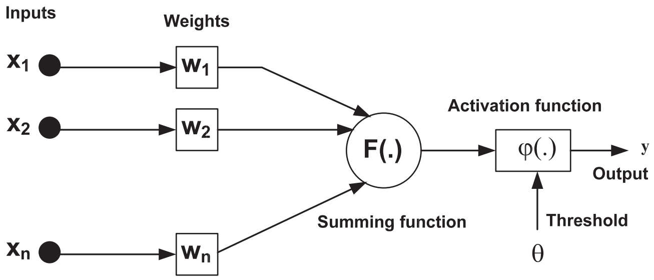

Fig. 1. The mathematical model of neuron.

network produces an associated output pattern. Its learning and update procedure is based on a relatively simple concept: the network is provided with both a set of patterns to be learned and the desired system response for each pattern. If the network generates the wrong answer, then the weights are updated to be less error. Finally, future responses of the network are more likely to be correct (Kermanshahi & Iwamiya, 2002).

Artificial intelligence methods could have been used in the stages of manufacturing. Machining is one of the basic manufacturing techniques used in the industry. Manufacturers must minimize cost and process time, and additionally, the product must comply with the required dimensions and quality criteria for a better competition (Asiltürk & Ünüvar, 2009). In this study, ANN structure shown in Fig. 2 is used for modeling and predicting surface roughness in turning operations. This fully connected hierarchical network structure has an input layer, a hidden layer, and an output layer. The back-propagation learning algorithms such as scaled conjugate gradient (SCG) and Levenberg–Marquardt (LM) are used to update the parameters in feed forward single hidden layers. The cutting speed (V), feed (f), and depth of cut (d) are considered as the process parameters. The input layers of the neural network consist of three neurons whereas the output layer has a single neuron that represents the predicted value of surface roughness.

Some parameters (i.e. the number of training and testing data, learning rate, number of hidden layers, and processing function used) affect the accuracy, reliability, and effectiveness of the neural network. It is seen that the processing functions, logsig and tansig, produce almost the same performance in different problems. The experiments show that the double hidden layer network has any advantage over single hidden layer network (Kohli & Dixit, 2005). Hence, only the logsig processing function and single hidden layer have been used. A trial and error scheme has been used to determine the appropriate number of hidden neurons. The number of hidden neurons was determined as four and five neurons. Since the input parameters were in different ranges, this parameters were normalized within 0.1–0.9 ranges in order to prevent the simulated neurons from being driven too far into saturation. The maximum number of epochs and the learning rate value for each run were selected as 10,000 and 0.9, respectively.

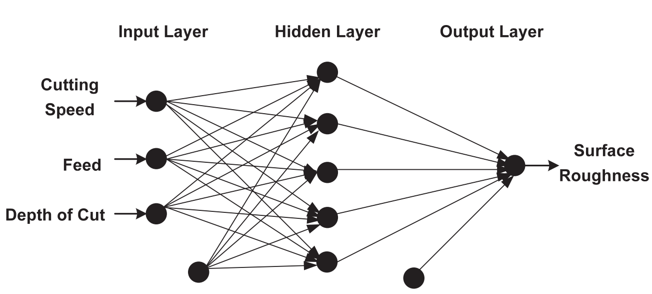

Fig. 2. ANN structure.

Ten independent runs having different initial random weights were performed to achieve a good solution. The error during the learning called as mean squared error (MSE) is calculated as follows:

$$MSE = \left((1/N) \sum_i |t_i - o_i|^2 \right) \tag{6}$$

where t is target value, o is output value, and p is pattern. The weights between hidden layer and output layer are adjusted and are again calculated using the chain rule of differentiation as follows:

$$\Delta w_{ji}(n) = \eta \delta_j(n) y_i(n) \tag{7}$$

$$\delta_j(n) = e_j(n) \varphi' \left(\sum_{i=0}^{m} w_{ji}(n) y_i(n) \right) \tag{8}$$

$$\delta_j(n) = \varphi' \left(\sum_{i=0}^{m} w_{ji}(n) y_i(n) \right) \sum_k \delta_k(n) w_{kj}(n) \tag{9}$$

$$\Delta w_{ji}(n) = \alpha \Delta w_{ji}(n-1) + \eta \delta_j(n) y_i(n) \tag{10}$$

where η is the learning rate parameter and α is the momentum coefficient.

2.4. Experimental setup

Data sets are from experiments conducted on a CNC turning machine in the laboratory of the Selçuk University, Konya, Turkey. The details of the machining experiments are given in Table 1. Single insert was used in the experiments for machining of AISI 1040 steel. After each turning operation, the surface roughness (Ra) was measured with Surface Roughness Tester Mitotoyo (SJ-301). The measurements were taken three times for each workpiece. A National Instruments portable E Series NI DAQCard-6036E with maximum acquisition rate of 200,000 samples per second and 16 channels, data acquisition card was used to transmit the data to PC. A software called as **ilhan_daq_v01** was developed using Matlab 6.5 program. The constants and cutting parameters were entered to the interface. The outputs were measured as 80 samples/sec, and their average values were recorded as one datum. Consequently, tests were performed with 27 experimental runs. The workpiece material in the tests was selected to represent the major group of workpiece materials used in industry. In this study, AISI 1040 working specimen was used. It is hardened to 35 HRC, and then normalization was made at 900 °C for the homogeneity of material. The specimen was cylindrical bar with 90 mm diameter and 60 mm length (measured from chuck to tail stock). The discontinuous or unexpected hardening distribution on specimens can appear due to the extrusion production process. Therefore in order to remove the outer layer, before the experiments, the specimens were turned with 2.0 mm cutting depth. The block diagram of the experiment set is shown in Fig. 3.

The cutting tests have been carried out on Moriseiki NL2500MC/700 lathe. The cutting tool MWLNR 25X25 is a

Table 1
Process parameters with their values at three levels.

Parameters	Level 1	Level 2	Level 3
Cutting speed (m/min)	150	219	320
Feed rate (mm/rev)	0.12	0.2	0.35
Depth of cut (mm)	1	2	4
Workpiece Material AISI 1040, 35 HRC	C = 0.44% P = 0.011%;	Si = 0.19% S = 0.01%;	Mn = 0.64%

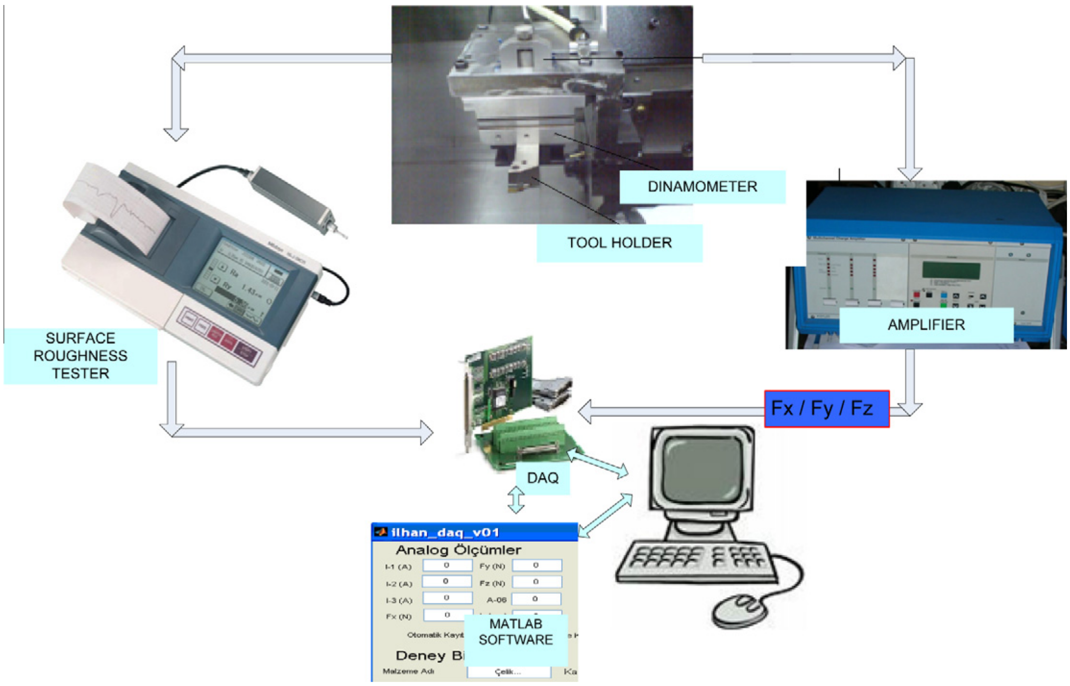

Fig. 3. Experimental setup.

commercial product available by Iscar Company. Carbide inserts with product number Tips WNMG 080408-TF MTCVD TiCN and a thick alpha Al_2O_3 CVD coating were used. The cutting parameters were selected so that the measured cutting forces would not exceed the upper limit of the dynamometer working rate. The cutting parameters suggested by cutting tool supplier are given in Table 1.

In order to keep the cutting conditions unchanged, each experiment was conducted with new sharp tools. The cutting tests were carried out without coolant, and totally 27 experiments were performed according to full factorial design. The roughness parameters generally depend on the manufacturing conditions like feed, depth of cut, cutting speed, machine tool, and cutting tool rigidity, etc. In this study, three main cutting parameters, cutting speed (V), feed (f), and depth (d) of cut are selected. Three level tests for each factor were used because the considered variables are multi-level variables and their outcome effects are not linear. Table 2 shows the experimental data for AISI 1040 steel.

Table 2
The experimental data for model constructions.

Test no.	V (m/min)	f (mm/rev)	a (mm)	Ra (μm)
1	150	0.12	1	1.02
2	150	0.12	2	1.18
3	150	0.12	4	1.12
4	150	0.2	1	1.68
5	150	0.2	2	1.34
6	150	0.2	4	1.83
7	150	0.35	1	3.55
8	150	0.35	2	3.52
9	150	0.35	4	3.5
10	219	0.12	1	0.79
11	219	0.12	2	0.93
12	219	0.12	4	1.13
13	219	0.2	1	1.66
14	219	0.2	2	1.61
15	219	0.2	4	1.85
16	219	0.35	1	3.75
17	219	0.35	2	3.8
18	219	0.35	4	3.86
19	320	0.12	1	0.74
20	320	0.12	2	0.9
21	320	0.12	4	0.97
22	320	0.2	1	1.91
23	320	0.2	2	1.9
24	320	0.2	4	1.93
25	320	0.35	1	3.67
26	320	0.35	2	3.69
27	320	0.35	4	3.82

3. Results and discussion

In this section, the results obtained from the multiple regression and neural networks are compared and discussed.

3.1. Multiple regression analysis

The data presented in Table 2 have been used to build the multiple regression model. The coefficients $\beta_0, \beta_1, \beta_2, \ldots, \beta_9$ are estimated with the least square method using MINITAB 14. Accordingly, the equation of the second-order fitted model for surface roughness is given as follows:

$$R_a = 0.130 + 0.00088V + 3.54f - 0.011a + 0.000005V^2 + 14.4f^2 + 0.0174a^2 + 0.00848V \times f + 0.000059V \times a - 0.194f \times a \quad (11)$$

The feed rate is the most dominant factor on the surface roughness, followed by the depth of cut and cutting speed, respectively. It is obvious that there is a good correlation (R^2 = 98.9%) between the surface roughness and cutting parameters. The significance of the multiple regression coefficients for second-order model (R^2, determination coefficient) is 0.989. It can be said that the second-order model can explain the variation with accuracy, 98.9%. Fig. 4 shows the comparison of measured and predicted data of the surface roughness for the multiple regressions. It is seen from Fig. 4 that there is a strong relationship between the predictor variables and response variable.

The ANOVA test was used to determine the dependency of surface roughness to selected machining parameters. Besides, the

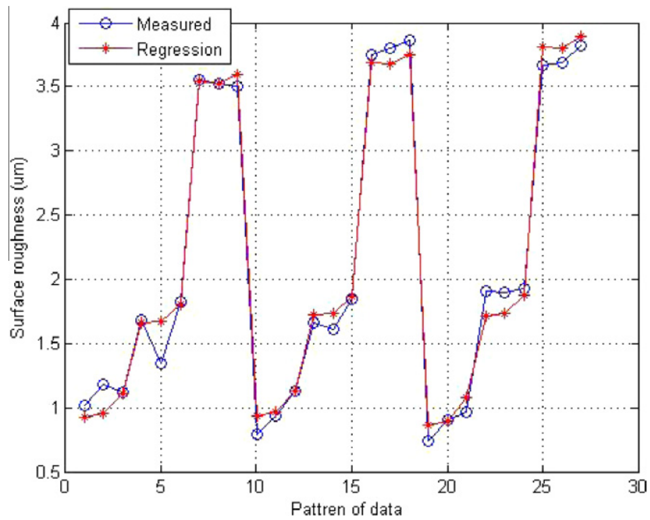

Fig. 4. Measured and predicted data of the surface roughness for multiple regression model.

main effects of these variables and the interactions of them were included to the analysis. The results of this test are shown in Table 3. It can be said from Table 3 that regarding the main effects, the greatest influence on the surface roughness is exhibited by the feed rate (f), followed by depth of cut (a) and cutting speed (V). Furthermore, $V * f$ shows the greatest contribution as the interactions. The ANOVA test was performed at a significance level of 5% i.e., confidence level of 95%. Since P value given in Table 3 is less than 0.05, the developed model is significant. According to the other hypothesis, if at least one of these coefficients is not equal to zero, the model will be accepted. It is seen from Table 3 that this hypothesis is confirmed.

3.2. Results of artificial neural networks

Multilayer perception structure that is a kind of feed-forward ANNs was applied to model and predict the surface roughness in turning operations. The experimental data presented in Table 2 were utilized to build the ANN model. The back-propagation training algorithms, the scaled conjugate gradient (SCG) and Levenberg–Marquardt (LM), were used for ANNs training. The best results were obtained with this algorithm compared to other training algorithms. Two ANNs structure, 3-5-1 and 3-4-1, were tested. This means 1 node output layer, 4/5 node hidden layer, and 3 node input layer for input variables. The neural networks software was coded using the Matlab Neural Network Toolbox. The learning parameters of the proposed ANN structure are presented in Table 4.

The experimental data set consists of 27 patterns, of which 21 patterns were used for training the network and 6 patterns were

Table 3
The results of ANOVA test for surface roughness.

Source of variance	DF	SS	MS	F	P
V	2	0.0391	0.0196	2.22	0.172
f	2	35.0708	17.5354	1986.18	0.000
a	2	0.1055	0.0527	5.97	0.026
$V * f$	4	0.3123	0.0781	8.84	0.005
$V * a$	4	0.0249	0.0062	0.71	0.610
$f * a$	4	0.0775	0.0194	2.19	0.160
Error	8	0.0706	0.0088	–	–
Total	26	35.7007	–	–	–

Table 4
The training parameters.

The number of layers	3
The number of neurons on the layers	Input: 3, Hidden: 4 and 5, Output: 1
The initial weights and biases	Randomly between −1 and +1
Activation function	Log-sigmoid
Learning rate	0.05
Momentum constant	0.95
The normalization of data	0.1–0.9
The number of iteration	10,000

chosen randomly for testing the performance of the trained network. After the network has successfully completed the training stage, it was tested with the experimental data that were not present in the training data set. The results obtained were compared using statistical methods. The performance criteria considered are the mean absolute percentage error (MAPE) and the determination coefficient (R^2)

$$MAPE = \left(\frac{1}{N} \sum_i \left| \frac{t_i - o_i}{t_i} \right| \times 100 \right) \tag{12}$$

$$R^2 = 1 - \left(\frac{\sum_i (t_i - o_i)^2}{\sum_i (o_i)^2} \right) \tag{13}$$

where N is the number of patterns.

The statistical error values for the ANN approaches are presented in Table 5. For the surface roughness, the best approach having the minimum error is achieved by SCG algorithm with five neurons. The activation function in this study is as follows:

$$F_i = \frac{1}{1 + e^{-E_i}} \tag{14}$$

where E_i is the weighted sum of the input parameters and is calculated as:

$$E_i = C_{1i} \times I_1 + C_{2i} \times I_2 + C_{3i} \times I_3 + C_{4i} \tag{15}$$

where I_1, I_2, and I_3 are the input parameters: the cutting speed, feed, and depth of cut, respectively. The coefficients (C_{ji}) are given in Table 6 for SCG algorithm with five neurons. The surface roughness is computed as follows:

$$Surface\_Roughness = \frac{1}{1 + e^{-(-0.23273F_1 - 1.05291F_2 - 0.25799F_3 - 1.48935F_4 + 0.184596F_5 + 1.87756)}} \tag{16}$$

Figs. 5 and 6 show the comparison of measured and predicted data of the surface roughness for the training and testing stages, respectively. The ANN results demonstrate that the proposed model in this study is suitable for predicting the surface roughness. The statistical values for ANN model, mean squared error (MSE), mean absolute percentage error (MAPE), and the determination coefficient (R^2) are in acceptable ranges.

3.3. Overall evaluation

A full factorial experimentation design is implemented to seek the effects of the cutting parameters (i.e. cutting speed, feed rate, and depth of cut) on the surface roughness. After each turning operation, the measurements of surface roughness were recorded. Artificial neural network and multiple regression models were developed to predict the surface roughness using the experimental data. Table 7 shows the comparison results according to accuracy values of multiple regression model and neural network model. The results are generally found to be close to the directly measured

Table 5
The statistical error values.

Algorithm neurons	Training data			Testing data		
	MSE	R^2	MAPE	MSE	R^2	MAPE
LM 4	0.001515	0.998892	1.765	0.0364991	0.990083	12.978
LM 5	0.001515	0.998881	1.867	0.0093580	0.993900	5.605
SCG 4	0.001429	0.998944	1.815	0.0186448	0.985537	8.870
SCG 5	0.001520	0.998875	2.533	0.0086907	0.994462	5.156

Table 6
The weights between input layer and hidden layer.

i	C_{1i}	C_{2i}	C_{3i}	C_{4i}
1	2.357161	−6.21031	11.90727	−8.83548
2	−1.39911	−5.7942	−0.16583	3.706887
3	1.138848	−7.19467	14.1882	0.141266
4	0.439956	1.044427	−1.11184	−0.12652
5	7.58048	−7.27693	−1.80273	6.055423

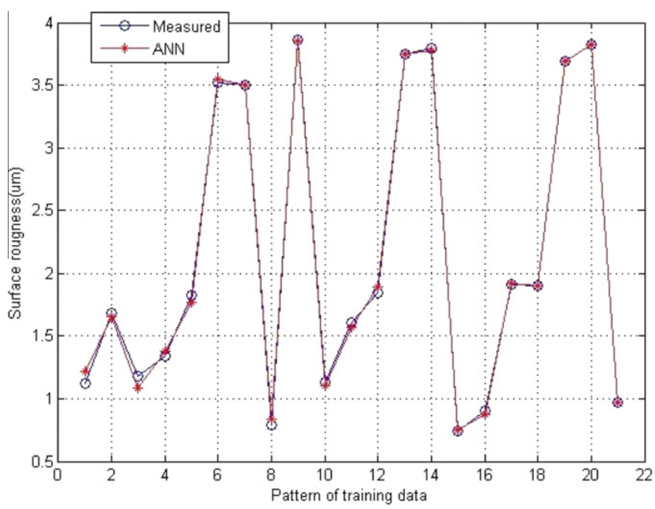

Fig. 5. Comparison of measured and predicted data of the surface roughness in the training stage.

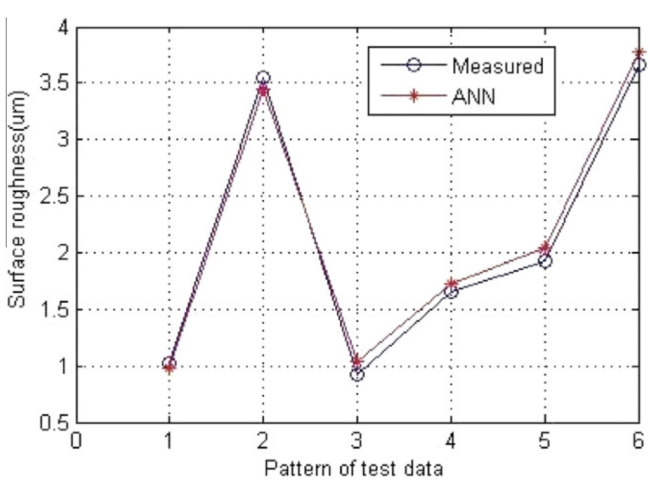

Fig. 6. Comparison of measured and predicted data of the surface roughness in the testing stage.

data for all methods. So the proposed models can be used effectively to predict the surface roughness in turning process. However, as can be seen from the performance criterion in Table 7, ANN produces the better results compared to multiple regression. It is important to note that the ANN model is very successful at the training stage but it is not good enough at the test data.

Table 7
Comparison of the models.

		MSE	MAPE	R^2
Multiple regression	Second-order model	0.018447	7.597	0.989232
Neural network	Training	0.001520	2.533	0.998875
	Testing	0.0086907	5.156	0.994462

4. Conclusions

In this study, multiple regression and artificial neural network approaches were used to predict the surface roughness in AISI 1040 steel. The parameters such as cutting speed, feed, and cutting of depth were measured by means of full factorial experimental design. The data obtained were used to develop the surface roughness models. The following conclusions can be drawn from the present study.

The feed rate is the dominant factor affecting the surface roughness, followed by cutting of depth and cutting speed.

The back-propagation training algorithms, the scaled conjugate gradient (SCG) and Levenberg–Marquardt (LM), were used for ANNs training. The best result having the minimum error was obtained by SCG algorithm with five neurons.

The developed models were evaluated for their prediction capability with measured values. The predicted values were found to be close to the measured values. The proposed models can be used effectively to predict the surface roughness in turning process. The determination coefficient (R^2) is 99.8% for training data and 99.4% for the testing data in neural network model, while it is achieved as 98.9% for multiple regression models.

Considering that advantages of the ANN compared to multiple regression are simplicity, speed, and capacity of learning, the ANN is a powerful tool in predicting the surface roughness.

In future researches, an economical study on a manufacturing facility may be conducted to investigate the benefits of implementing ANN and multiple regression models in the turning process.

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