Prediction of Surface Finish Model in Cutting AISI 4140 Steel with Different Approaches

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Abstract This experimantel study describes the development of surface roughness model with main parameters including tool radius using full-factorial design approach and artificial neural network (ANN). Cutting tests and analysis of variance were used in cutting AISI 4140 steels by coated cutting tools. Factorial design/multi quadratic regression (MQR) were compared to ANN model. The results indicated that surface finish decreased with decreasing feed rate and increasing nose radius. It is showed that both feed rate and tool nose radius were effective while other factors were insignificant effect. For testing stage of both methods, data was selected randomly from the existing experimental runs. Further, both randomly selected ANN and MQR indicated no significant differences for prediction the surface roughness because PE and RMSE were 2.73%, 2.21%, 0.063 and 0.046 for MQR and ANN, respectively. Both approaches can used effectively for prediction of any machinability studies in manufacturing engineering due to high accuracy of results. In the future work, other nonlinear models like support vector machine and principal component analysis would be conducted to improve performance accuracy.

Keywords Surface finish · Alloy steel · Coated carbide tools · Cutting · Full factorial design · ANN

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1 Introduction

Turning is the most important production process in metal cutting processes because of its complexity and generating high cutting temperatures between tool inserts and workpiece. Productivity can be increased with this type of machining process. To increase productivity and reduce the manufacturing costs in turning process, an appropriate machining parameters can be selected, but cutting with high productive may be reduced the efficiency of machining process and output of quality characteristics. In the past few decade, there have been many developments of carbides or ceramics for machining various hard and hardened materials including cast irons. Coated tools indicate a better wear resistance, lower heat and lower forces during machining. This is, especially true for better performance under heavy machining parameters when compared to uncoated tools [1].

Surface roughness parameter is one of the basic concern of metal cutting processes for characterizing the surface features. Cutting parameters, workpiece material, tool types, tool shapes and vibrations affect the surface finish [2]. Quality of surface finish plays a key role for machining different applications because of its effecting on fatique behaviour, while machining cost leads to higher. Among available method, center line average (CLA or Ra) is the most widely accepted measurement of surface finish. For any metal cutting processes, unless appropriate conditions are chosen, lower roughness and right dimensional size can not be achieved. Thus, number of studies have been conducted in past three decades for determining the optimal machining conditions [1, 3]. Their experimental results indicated that it reduced with enhanced speed and depth of cut, respectively. Davim [4] indicated that larger effect was obtained from speed, but feed rate and depth of cut had no effective on surface finish. Escalona and Cassier [5] exhibited that surface roughness improved with speed, nose radius by reducing feed rate when developed roughness model for some steels. An empirical model for surface finish was developed through factorial design depending upon hardness of workpiece, feed rate, tool's point angles, speed and cutting time [6]. Transformation of logaritmic scale data and nonlineer regression analysis were applied on the empirical developed model. The developed model indicated a satisfactory results for both generating model and confirmation tests due to producing lower errors when compared to existing research. Suresh et al. [7] studied the AISI 4340 steel and Wang and Zheng [8] searched the hardened AISI H13 steel using coated carbide and TiAlN coated carbide tool, respectively. Higher speed and lower feed rate were minimization of the surface finish. Power/tool wear increased linearly with increasing speed and feed rate. Further friction coefficient and chip shearing energy were larger for ductile materials. Moreover, different models for surface roughness were developed using factorial/Taguchi method in turning various steels using carbide/coated carbide cutting tools [9–13].

Further, there have been numbers of surface roughness optimization models for ceramic cutting tools on cold-work, hot work and bearing steels [14–20]. Junaid and Wani [14] studied the surface finish of cutting AISI D2 steel by boron nitride, ceramic and coated tools conducting tests through RSM approach. Quadratic regression equation was generated to examine the relationship between inputs and responses. The results showed that the dominant factor was cutting time and cutting speed, respectively. Davim and Figueira [15] performed a machinability test for AISI D2 tool steels having hardness 60 HRC using statistical investigation. Cutting tests were carried out with wiper and traditional ceramic tools. Basic factors affecting the flank tool wear of ceramic tools were time and speed. A better performance was revealed with wiper ceramic tools than that of traditional tools. Aouici et al. [16] observed that feed rate was most effective in terms of depth of cut for hard turning AISI D3 hardened steel with ceramic base on turning force/power. The minimum force and better surface finish were achieved at around 0.12 mm/dev. feed rate associated with higher speed and lower depth of cut. Bensouilah et al. [17] observed the machining AISI D3 steel through coated and uncoated CC650 ceramic tools. The better surface quality was obtained with coated ceramic insert (1.6 times) than that of uncoated CC650 ceramic. Elbah et al. [18] studied these two types cutting tools for cutting AISI 4140 steel. Their results indicated that wiper ceramic tool's performance was 2.5 times better than that of uncoated ceramic tool. Further, RSM has been studied widely with some other researchers on surface finish models [21, 22].

Moreover, number of studies have been performed in terms of tool nose radius besides main parameters [23–38]. Effect of the tool's radius were studied during the machining results for tough materials [23, 24]. It was observed that surface finish was highly affected with nose radius. It is found that increasing tool's nose radius led to higher difference between surface tensile stress and sub-surface compressive stress. Chou and Song [25] investigated the turning process with changing tool's nose radius and feed rates. Higher nose radius indicated a finer surface roughness while feed rate strongly affected the surface quality. Ranganath and Vipin [26] studied the surface roughness in terms of design of experiments. The surface finish decreased by increasing speed and reducing by enhanced nose radius. Ranganath et al. [27] predicted the surface finish in cutting EN8 steel by uncoated carbide inserts with RSM. Second order model indicated a quite good result for predicted and measured surface finish. Nataraj and Nagarajan [28] studied the machining EN31 alloy steel under wet condition based on speed, feed rate and nose radius. It is formed theoretical model with RSM to reduce the surface roughness and increase volume of the material. Their results exhibited that surface finish decreased with increasing nose radius. These findings were not only true for different steels as mentioned above, but also for Al 6061 alloy, TiB2/7075 Al alloy composites and Inconel 718 alloy [29–32]. In the composites, cutting force increased with increasing nose radius and caused to lower surface residual stress and more deep residual stress for penetrated layer. Maximum residual stress position transferred to deep surface from machining top surface while tool wear increased. Cutting force, microstructural changes and residual stress distributions were analyzed. They concluded that enhancing tool nose radius resulted in increasing cutting force and increased depth of deformation layers and more higher surface tensile stresses occurred [33, 34]. Taha et al. [35] observed the effects of insert geometries on surface finish in cutting AISI D2 steel. Measured surface roughness and theoretical surface finishes of two different inserts like 'C' and ’T’ type were compared. Surface roughness was lower for ’C’ type insert than that of ’T’ type under 0.4 mm/rev feed rate. It is concluded that cutting parameters in addition to tool’s nose radius were effective. Agrawal et al. [36] studied the AISI 4340 steel with 69 HRC using CBN cutting tools under dry conditions. Three regression models like multiple-, randomly forestry and quantatity regression. Spindle speed was effective on the surface finish among parameters. Randomly oriented forestry model was found to be better than that of multiple regression model. Liu et al. [37] studied tool’s effect on radius of nose and tool wear of JIS SUJ2 bearing steels with CBN tools in terms of residual stress distributions. X-Ray Diffraction method revealed the radius of tool nose affecting on residual stress distributions. Whereas, the residual squeezed stress increased largely under machined surface when wear of tool increased. Dhar et al. [38] searched the effect of tool wear on the surface quality of mild steel (AISI 1060) in cutting at various conditions. Trends in average Ra values increased with cutting time and tool wear. In addition, higher Ra values were observed with wet cutting than that of dry cutting.

Predicting surface finish models was made using response surface methodology (RSM), fuzzy logic (FL), multiple regression analysis (MRA) and artificial neural network (ANN). Akkuş and Asilturk [39] studied that surface roughness was carried out with various parameters and compared to hard turning with ANN, FL and MRA. It is indicated that FL method was better for optimum predictive model than that of ANN based on mean squared errors. Davim et al. [40] examined the surface finish model for prediction with ANN method. Process parameters for this model were basic cutting factors with three levels according to L27 orthogonal arrays. It was indicated that surface roughness reduced significantly with speed and feed rate while increased with depth of cut. Ozel and Karpat [41] developed an ANN model to estimate the wear and surface finish. Experimental results were used with Leven berg–Marquardt training. The model applied was found to be better when compared to empirical model. The results indicated that better results could be obtained from ANN with single output in comparison to ANN with multiple output. Rajeev et al. [42] worked the surface finish in turning hardened low alloy steel (AISI4140) with 47 HRC by central composite design. Prediction model for surface finish was developed with MRA and ANN. The results showed that more accuracy was provided with ANN model compared to regression. Chavoshi and Tajdari [43] searched the machining of AISI 4140 steel in cutting by Cubic Boron Nitride tools. They conducted 18 experiments, but keeping the depth of cut and feed rate fixed. These models were used in specifying the optimum parameters. The results indicated that significant factor was hardness on the roughness. Dimla and Lister [44] developed the multilayer perception network for predicting wear using force and acceleration for AISI 4340 steel. Similar studies on carbon steels using different design were carried out with the previous researchers [45–49].

The purpose of the experimental study is, thus, to estimate theprediction of surface finish with factorial design. Coated carbide cutting tools were selected in machining of AISI 4140 steel at dry conditions, and developed a second-order quadratic model (MQR). In addition, MQR and ANN method were compared in terms of root mean squared error (RMSE) and percentage error (PE).

2 Materials

2.1 Theoretical Model

Second order model (quadratic) for surface finish can be generated from the formula following;

$$\begin{aligned}
&\hat{y} = y - \varepsilon = b0. \times 0 + b1. \times 1 + b2. \times 2+\\
&b3. \times 3 + b4. \times 4 + b11. \times 12 + b22. \times 22\\
&+b33. \times 32 + b44. \times 42 + b12. \times 1. \times 2\\
&+b13. \times 1. \times 3 + b23. \times 2. \times 3 + b24. \times 2. \times 4 + b34. \times 3. \times 4
\end{aligned} \tag{1}$$

where; b values are estimates of β parameters, ε is experimentally random error, parameters of Eq. (1) were estimated through a Minitab computer software system.

2.2 Workpice Material and Design of Experiments

The used material of the study was an AISI 4140 steel. Table 1 indicates the chemical compositions of elements in AISI4140 steel (wt.%) used for machining tests under various cutting conditions. Cylindrical shape of specimens, which is 120 mm diameter, 280 mm length were studied in these tests. Cylindrical bars were cut at dry condition. Before actual machining tests, the bars were cleaned by removing about 1–2 mm from outside the specimen surface.

In order to improve a second order model, a method was made with factorial approach, which is consisted of 54 experiments. Two levels for each variable were denoted by –1, 0, + 1 that was used for augments points. Full factorial design was chosen so that all interacted variables would be found out. Four factors like speed, feed rate, depth of cut and nose radius were considered. Cutting conditions and levels of each factors for turning to be used for this study are presented in Table 2.

Table 1 Chemical compositions of elements in AISI4140 steel (wt.%)

Elements of weight percentages (wt.%)							
C	Si	Mn	Cr	Mo	Ni	Cu	Fe
0.40–0.50	0.236	0.816	0.989	0.16	0.144	0.18	97

Table 2 Cutting conditions and their levels in turning application

Factors	Units	Levels		
		− 1	0	+ 1
Cutting speed (X_1)	$m.min^{-1}$	300	375	450
Feed rate (X_2)	$mm.rev^{-1}$	0.1875	0.25	0.3125
Depth of cut (X_3)	mm	0.5	1	1.5
Tool's nose radius (X_4)	mm	0.8	–	1.2

2.3 *Cutting Tools/Measurement*

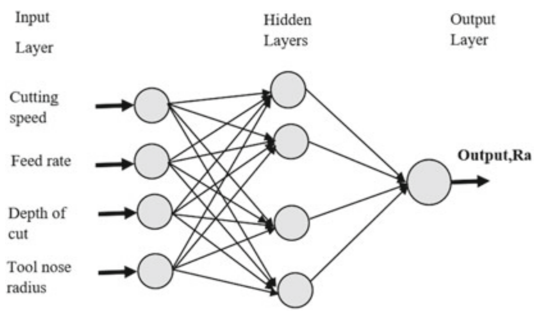
Industrial type of CNC lathe machine (Johnford TC35) was used for turning tests. Spindle speeds varied from 50 to 3500 rpm. The tools selected for the experiments were coated carbide cutting tools, which are manufactured on substrate cemented carbide tool with chemical vapor deposition (CVD) technique, called as TP100. Carbide tool has a multiphase coatings including Ti (C,N) + Al2O3 + TiN here. Insert types were TNMG 160,412-MF2 and TNMG 160,408-MF2, respectively. These were provided from Seco Inc. for cutting tests.

A MAHR Perthometer-M1 type of portable was used to measure the surface finish of mild steel. Ra is defined as an arithmetic mean deviation of roughness profile. Three measurements are taken along the axis of specimen to collect the surface finish of cylindrical shaft.

2.4 *Artificial Neural Network (ANN)*

ANN works through a learning algorithm by adjusting weights and biases that reduce the error through activation function [50]. To develop model, four parameters were taken as input criterions such as speed, feed rate, depth of cut and nose radius while output was surface roughness. Each network composes of three layers like input, output and hidden layer, as shown in Fig. 1. ANN was implemented using the

Fig. 1 ANN architecture



developed feed-forward backpropagation (BP) network (4–5–1). Many activation functions were used to train algorithms of ANN.

The data [9] was normalized between 0 and 1 according to Eq. (2). Data were split into training (80%) and testing (20%) stage. Input and output data were used between 0 and 1 according to Eq. (2),

$$N = \frac{\beta_1 - \beta_{min}}{\beta_{max} - \beta_{min}} \tag{2}$$

where N is normalized data; βi is measured data while βmin, βmax show minimum and maximum values, respectively. Normalisation gives an equal result for whole factors.

Model's performance were evaluated in terms of RMSE and PE through Eqs. (3), (4), respectively.

$$RMSE = \sqrt{\sum_{i=1}^{N} \frac{(Q_o - Q_p)^2}{N}} \tag{3}$$

$$\text{PE} = \frac{Qo - Q_p}{Qp} \times 100 \tag{4}$$

which Qo, Qp and Qm are the obtained result, estimated and mean results, respectively. When R^2 approaches to 1 and RMSE gets closer 0, it means that higher efficiency and high performance can be achieved for model formed.

The experimental data for surface finish of alloy sample was collected from total 54 measurements performed in the past study [9].

3 Results and Discussion

3.1 Surface Roughness

Minitab software analysed the data. Second order regression (MQR) equation can be found in the following equation, but × 1 and × 3 are not effective. Therefore, they are neglected.

The second order model equation is given by;

$$\text{Ra}, \mu\text{m} = 0.154 + 1.240\text{X2} + 0.4203\text{X4} + 0.1519\text{X2} * \text{X2} - 0.6242\text{X2} * \text{X4} \tag{5}$$

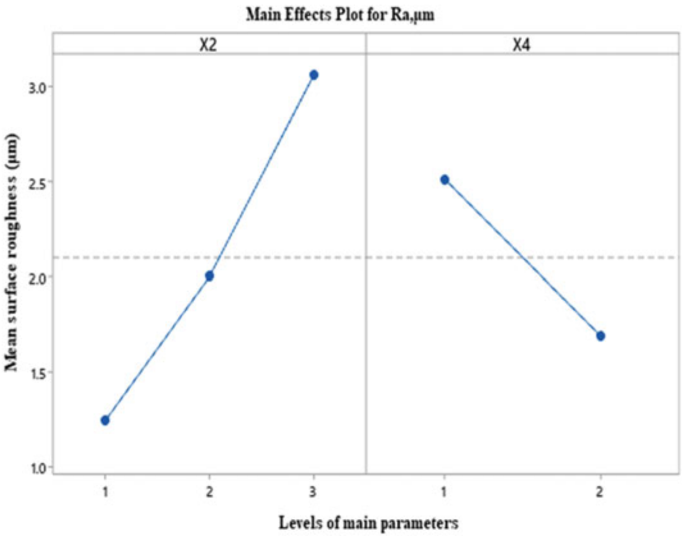


Fig. 2 Main effects plot for Ra values

Equation (5) showed that feed rate (×2) and tool nose radius (×4) had positive effects on surface finish when used TiN-coated tools. The model had an adjusted R^2 value of 98%.

Figure 2 indicates the main effects plot for Ra values of tested samples. It can be shownn in this figure, feed rate was more effective than that of tool nose radius because it improved by reducing surface roughness while it reduced with enhanced the nose radius. In other words, a better surface finish was achieved using lower feed rate or bigger tool's nose radius. Similar findings were reported within previous studies [23–26, 28, 29]. The variations of these paramateres on Ra values were changed more or less linearly.

Pareto chart is one of the basic quality tools for analysing data among factors. Figure 3 indicates the Pareto chart for standardise influence of factors on the surface finish of tested steels. In this chart, the length of bars visually revealed the degree of effect of each parameter for observed results. As was shown in this figure, the Pareto chart indicated that increase of B, D (X2, X4) main parametres, BB quadratic and BD interaction factors had a positive, statistically important effect on the surface finish of tested specimens. This model's adequacy could be examined by the observation of residuals.

The surface finish for steel specimens with normal probability plot residuals are indicated in Fig. 4. This graph shows a cumulative distribution of standardised residuals that determine from theoretical and measured results. The error distributions seemed to be normal since these were appropriated for both positive and negative side of trials. Whereas, plots have had intervals, especially for forward points that had not dropped exactly along the straight line passing through the center while the

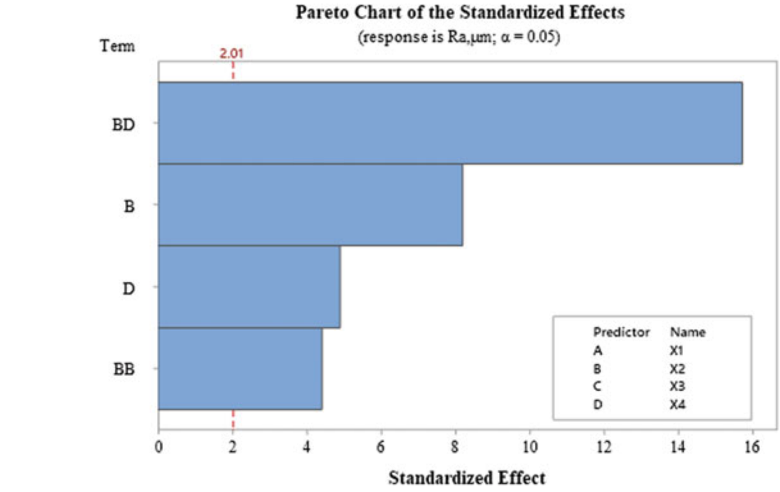


Fig. 3 Pareto chart for control factors of B,D and their interactions of BD

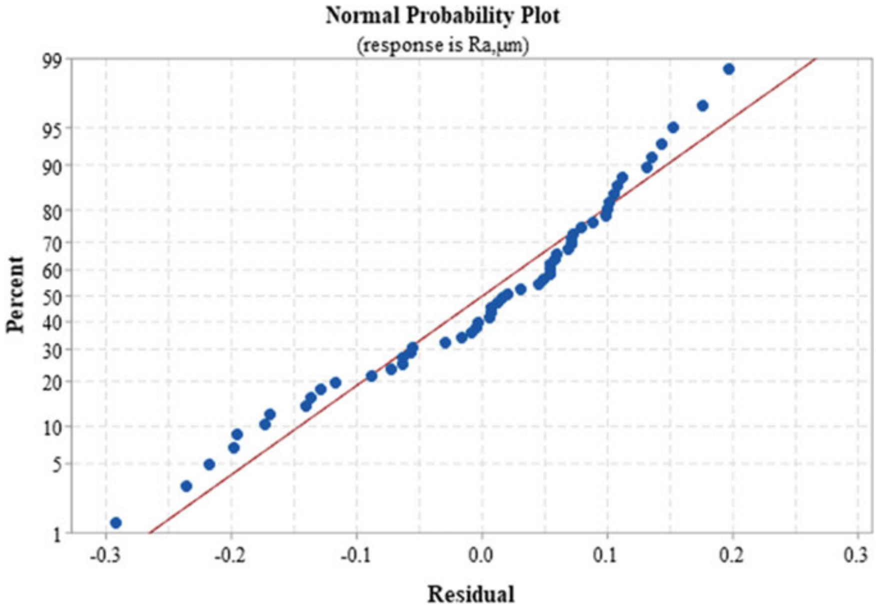


Fig. 4 Normal probability plot of residuals for surface roughness data in turning steels

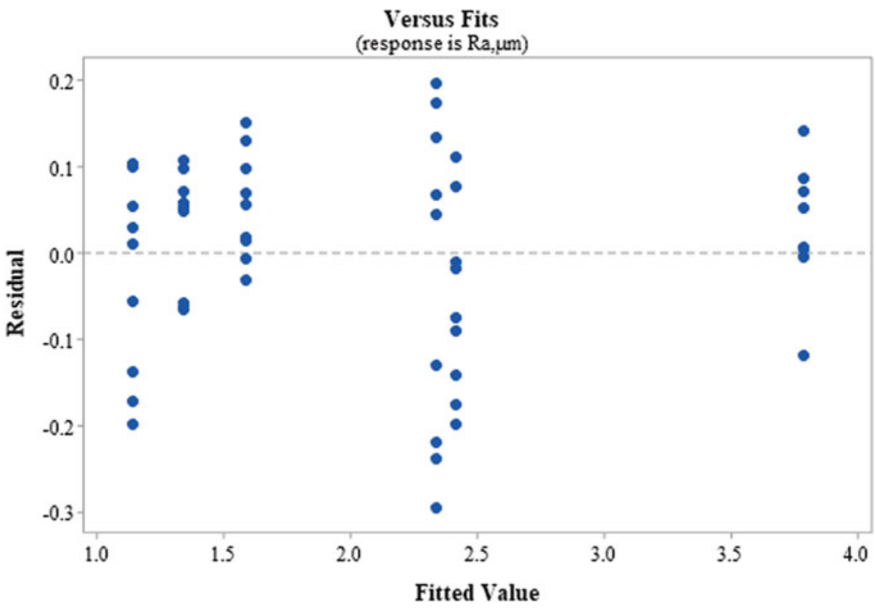


Fig. 5 Residuals plot versus Fitted Values of surface roughnesses

deviations from the normality had not seemed to be large. These results indicated that the model was adequate because of the residual points on probability. Standardised residual was about ±2.5.

Figure 5 indictaes the residuals plot versus fitted values of the surface roughness. These residuals vs.fitted values data should not indicate any obvious patterns and they had no usual structure, which indicated an adequate model. The residual seemed to be scattered randomly around zero line [21, 23].

3.2 Analysis of Variance (ANOVA)

ANOVA was selected to observe that control factors affecting on steel surface finish quality. ANOVA results for the surface finishes of Ra in machining steels under different parameters are demonstrated in Table 3.

The probability values (p-values) of the model were about 0.0 and 0.0 for X2 and X4 factors, respectively. In this table, smaller result of p-values signified that the related regression coefficient was very important. It meant that both nose radius and feed rate were effective to surface finishes. It is concluded from this work that surface roughness was highly affected by feed rate, followed by nose radius of tools [3, 7, 32]. However, there were no absolute agreements among the researchers. Davim [4], Ranganath and Vipin [26], Agrawal et al. [30] concluded that cutting speed was effective factor on the surface finish, whereas, other studies indicated that cutting

Table 3 Variance for Ra values analysis for second order model

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	4	42.9547	10.7387	755.10	0.000
X2	1	0.9546	0.9546	67.12	0.000
X4	1	0.3407	0.3407	23.96	0.000
X2*X2	1	0.2770	0.2770	19.48	0.000
X2*X4	1	3.5066	3.5066	246.57	0.000
Error	49	0.6969	0.0142		
Total	53	43.6516			

time was the effective factor, followed by cutting speed when turned AISI D2 steel using various cutting tools [14, 15].

3.3 *Comparison of Factorial and ANN*

The surface roughness results of two models such as MQR and ANN models are compared and presented for all testing stages in Tables 4 and 5 based on R2, PE and RMSE criteria. Figures 6 and 7 exhibit the comparison of the experimental and predicted results for surface finishes against randomly selected experimental run for testing of MQR and ANN outputs, respectively.

Table 4 Comparison of the experimental and predicted results of surface roughness values through randomly selected tests data for testing of MQR model

Trial number	Randomly tests	Exper., Ra (μm)	Theor., Ra(μm)	Percentage Error (PE), %
1	5	1.396	1.342347	3.996954588
2	9	2.3255	2.414083	3.669426445
3	11	2.3405	2.414083	3.048072498
4	13	3.6725	3.789681	3.092107225
5	19	1.414	1.342347	5.337889532
6	28	1.556	1.586028	1.893283095
7	29	2.405	2.414083	0.376250527
8	33	3.862	3.789681	1.908313655
9	43	2.273	2.414083	5.844165259
10	49	3.8435	3.789681	1.420145917
11	51	3.797	3.789681	0.193129712
11	54	2.3825	2.337431	1.928142478
		Average error, %		2.73

Table 5 Comparison of the experimental and predicted results of surface roughness values through randomly selected tests data for testing of ANN model

Trial number	Randomly tests	Exper.Ra (μm)	Theor.Ra (μm)	Error, %
1	5	1.396	1.380933408	1.091044084
2	9	2.3255	2.273858264	2.271106211
3	11	2.3405	2.316227352	1.047938931
4	13	3.6725	3.573510782	2.770083102
5	19	1.414	1.586872236	10.89389755
6	28	1.556	1.501875556	3.603790186
7	29	2.405	2.42486775	0.819333333
8	33	3.862	3.87660827	0.376831205
9	43	2.273	2.242473557	1.361284404
10	49	3.8435	3.882511519	1.004801112
11	51	3.797	3.786990151	0.264322034
12	54	2.3825	2.356811338	1.089975309
		Average error, %		2.21

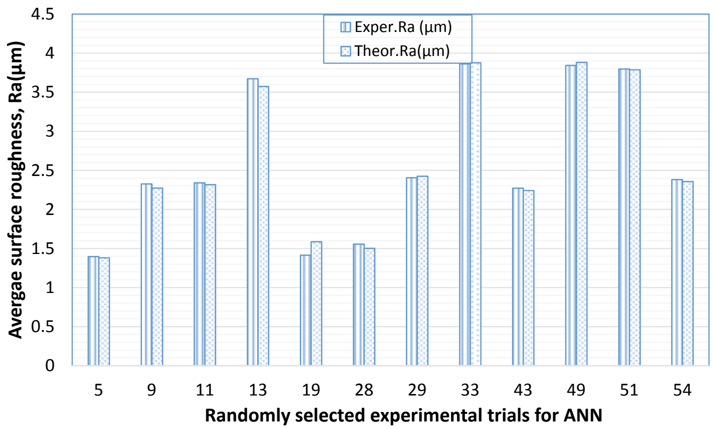


Fig. 6 Comparison of surface roughness between the experimental and predicted factorial results against selected experimental run for testing

The data were randomly selected such as 5, 9, 11, 13, 19, 23, 28, 29, 33, 43, 49, 51 and 54 for testing runs, as shown in Tables 4 and 5 for both designs. This figure demonstrated that there were some differences between the experimental and theoretical prediction values for testing algorithm. Error percentages in results of the surface roughness of steel for MQR and ANN were estimated. Percentage error (PE) was calculated using the data from experimental run - theoretical ones, divided by theoretical run $\times$ 100 .

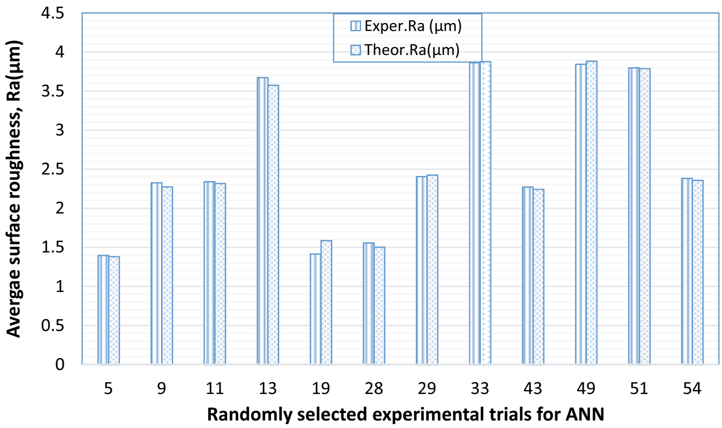


Fig. 7 Comparison of surface roughness between the experimental and predicted ANN results against selected experimental run for testing

The average error reached to 2.73% for MQR approach. This might be because more flucttutations appeared among the measured surface roughness values that was ranged from 0.1931 to 8.431 μm, but most of the data was around 1.9–3.6 μm except a few data like 5,10 and 11. Figure 7 also indicates the comparison between the experimental surface finish and corresponding ANN outputs. Although same data points were used again, there was small differences between the experimental and theoretical one, which are ranged from 0.095 to 4.16 μm, but most of the data was around 0.81–2.27 μm except a few data like 6,5 and 7. The average error was about 2.21% for ANN method due to nonlinear behaviour. Therefore, randomly selected ANN data provided a litte more precise results than that of randomly selected MQR. These models indicated a strong correlation between the input and output because the PE was 2.73% for MQR while it was % 2.21 for ANN, respectively. In terms of R2 criteria, there was no significant variations provided between ANN and MQR for selected run data. RMSE were about 0.063 and 0.046 for MQR and ANN, respectively. The previous study indicated that the fuzzy logic model was found to be better prediction model than that of ANN in terms of only MSE criteria [39]. In contast, applications of ANN were shown better estimations for other studies [41, 42]. As a summary, a comparison made between two different methods, as shown in Tables 4 and 5 and Figs. 6 and 7, ANN methodology gave a slightly better prediction results for Ra values.

It was obvious that Ra values predicted by MQR were found to be very close to experimental values of ANN results due to carrying out 54 experiments.

4 Conclusions

This study describes the improved of surface roughness models when cutting alloy steels (AISI 4140) using coated cutting tools at various dry conditions. Second-order method prediction equation was developed through full-factorial design of experiment and compared with ANN approach for RMSE, R^2 and PE. The experimental conclusions exhibited that surface quality enhanced with decreasing feed rate, but decreased with increasing nose radius. Variance analysis indicated that both feed rate and tool nose radius were effective on the surface finishes while other factors were in-significant. Moreover, in testing stage, randomly selected ANN exhibited a slightly better prediction ability than that of MQR because the average errors were 2.21 and 2.73% for ANN and MQR, respectively. Further, RMSE values were about 0.063 and 0.046 for MQR and ANN, respectively. Both methods can be used effectively for prediction tools in any types of machining applications in industry because of the high accuracy of the results. In the future work, other nonlinear models like support vector machine and principal component analysis would be performed for improving the accuracy of performance.

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