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RESEARCH ARTICLE - MECHANICAL ENGINEERING

Prediction of Surface Roughness for AISI 304 Steel with Solid Carbide Tools in End Milling Process Using Regression and ANN Models

S. Kalidass · P. Palanisamy

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Abstract This paper focuses on two different models, namely regression mathematical and artificial neural network (ANN) models for predicting surface roughness. In the present work, surface roughness is taken as the response (output) variable measured during milling, while helix angle, spindle speed, feed and depth of cut are taken as input parameters. The design of experiments (DOE) technique is developed for four factors at five levels to conduct experiments. Experiments have been conducted for measuring surface roughness based on the DOE technique in a vertical machining centre on AISI 304 steel using an uncoated solid carbide end mill cutter. The experimental values are used in Six Sigma software for finding the coefficients to develop the regression model. The experimentally measured values are also used to train the feed-forward back-propagation ANN for the prediction of surface roughness. Predicted values of response by both models, i.e. regression and ANN, are compared with the experimental values. The predictive neural network model was found to be capable of better predictions of surface roughness within the trained range.

Keywords Surface roughness · Regression model · Artificial neural network · End milling · Solid carbide tools

S. Kalidass (✉)
Department of Mechanical Engineering, Dr. N.G.P. Institute of Technology, Coimbatore 641048, Tamil Nadu, India
e-mail: skali_dass@yahoo.com

P. Palanisamy
Department of Mechanical Engineering,
Annai Mathammal Sheela Engineering College,
Erumapatty, Namakkal 637013, Tamil Nadu, India
e-mail: ppalanisamy2003@yahoo.com

الخلاصة

تركز هذه الورقة العلمية على اثنين من النماذج المختلفة المسماة بنماذج الانحدار الرياضي والشبكة العصبية الاصطناعية للتنبؤ بخشونة السطح. وفي هذا العمل الحالي يتم أخذ خشونة السطح باعتبارها متغير استجابة (مخرجات) تقاس في أثناء الطحن ، في حين تؤخذ الزاوية اللولبية ، وسرعة الدوران ، والتغذية وعمق القطع كمعلمات إدخال. وتم تطوير تقنية تصميم التجارب لأربعة عوامل عند خمسة مستويات لإجراء التجارب. وقد أجريت تجارب لقياس خشونة السطح على أساس تقنية تصميم التجارب في مركز قطع عمودي على فولاذ ايسي 304 باستخدام قاطع هاون ذي نهاية كربيد صلب غير مطلي. وتم استخدام القيم التجريبية في برمجية ستة سيغما لإيجاد المعاملات لتطوير نموذج الانحدار. وتم أيضاً استخدام القيم المقاسة معمليا أيضا لتدريب انتشار التغذية إلى الأمام وإلى الخلف في الشبكة العصبية الاصطناعية للتنبؤ بخشونة السطح. وتمت مقارنة القيم المتوقعة للاستجابة من كلا النموذجين ؛ أي الانحدار الرياضي والشبكة العصبية الاصطناعية مع القيم التجريبية. وقد وجد أن نموذج الشبكة العصبية التنبؤي قادر على تنبؤات أفضل لخشونة السطح ضمن النطاق التدريبي.

1 Introduction

In manufacturing industries, milling is a fundamental metal-cutting operation and end milling is the most frequent operation encountered, which was employed for making profiles, slots, engraves, contours and pockets in various components. Surface roughness is an important parameter in milling, which decides how the work piece components interact with its assembled parts. Obviously, rough surface will wear more and have high coefficient of friction than smooth surface; hence, surface roughness is a good predictor of quality of product. The demands for high quality of product relay on surface roughness urge the industrial automation to focus its attention on the surface finish of the product. Though surface roughness is a prominent parameter, it is expensive to control since the manufacturing cost will increase exponentially with decrease in surface roughness.

An effective model to predict the surface roughness becomes essential to ensure the desired quality in end milling. Various studies have been made on the surface roughness in end milling using various tools, work materials and experimental methods. The literature survey pertaining to the work of other researchers is indicated here. Mathematical models to predict surface roughness in terms of machining parameters such as spindle speed, feed rate and depth of cut have been developed by many researchers [1–4]. Thangavel and Selladurai [5] employed response surface methodology to predict surface roughness with the turning factors, such as cutting speed, feed rate, depth of cut and tool nose radius, and the model was checked for adequacy by analysis of variance. A multiple regression model was developed to predict the surface roughness of the machine surface by relating to spindle speed, cutting feed rate and depth of cut [6]. Influence of machining parameters, viz. spindle speed, depth of cut and feed rate, on the quality experimental evaluation of surface roughness for end milling of Al 6063 of surface produced in CNC end milling was investigated based on the response surface method [7]. Ginta et al. [8] employed central composite design of response surface methodology (RSM) to develop an analytical model for surface roughness in terms of cutting parameters, such as cutting speed, axial depth of cut and feed per tooth. Alauddin et al. [9] have developed the mathematical model of surface roughness for the end milling of 190 BHN steel, considering the centre line average (CLA) roughness parameter (Ra) in terms of cutting speed, feed rate and depth of cut using RSM. Ertekin et al. [10] have considered three different materials, viz. 6061 Al, 7075 Al and ANSI 4140 steel for roughness (Ra) study in CNC milling. Bhattacharya et al. [11] used Taguchi orthogonal array and analysis of variance to investigate the effect of cutting speed, feed rate and depth of cut on surface roughness and power consumption in high-speed machining. The first-order and second-order mathematical models, in terms of machining parameters tool geometry (radial rake angle and nose radius) and cutting conditions (cutting speed and feed rate) on machining performance, were developed based on Taguchi's experimental design method [12]. Ansalam Raj and Narayanan Namboothiri [13] proposed improved genetic algorithm (IGA) to optimize the cutting parameters, namely nose radius, feed, speed and depth of cut for predicting the surface roughness. Yang et al. [14] developed a Fuzzy-Nets-based in-process Adaptive Surface Roughness Control (FN-ASRC) system to adapt cutting parameters in process to improve the surface roughness of machined parts. The grey–Taguchi method was adopted to optimize the milling parameters of aluminium alloy with multiple performance characteristics and found that surface roughness decreased from 0.44 to 0.24 µm [15]. A predictive model of surface roughness was created based on the experimentally measured values with cutting speed, feed rate, depth of cut and material removal rate and further optimized to obtain minimum surface roughness by neural network and genetic algorithm [16]. Brezocnik et al. [17] proposed genetic programming approach to predict the surface roughness in end milling. Chang and Lu [18] proposed different polynomial networks for predicting surface roughness using the abductive modelling technique and the input variables selected based on F-ratio. Lo [19] used adaptive-network-based fuzzy inference system to predict surface roughness in terms of spindle speed, feed rate and depth of cut. Pal and Chakraborty [20] developed a neural network model to predict surface roughness in terms of cutting force, feed force, cutting speed, feed and depth of cut. Sivasakthivel et al. [21] have observed that the helix angle plays a significant role in surface roughness in the case of aluminium alloy (Al 6063) using high-speed steel end mill cutter. Kadirgama et al. [22] developed potential support vector machine (PSVM), and it is used to find the surface roughness when milling aluminium alloys (AA6061-T6) with carbide coated inserts. Design of experiments method and response surface methodology techniques are implemented. It is observed that the developed model is within the limits of the agreeable error (about 2–9 %) when compared to the experimental results.

The literature survey reveals that the predictive model of surface roughness is mostly based on empirical model with arbitrary assumptions. The geometrical variations of the solid carbide end mill cutters have not been included in most of the models. The effect of tool geometry (helix angle) has not been explored in detail. In this work, the main objective is to develop a mathematical model and neural network model to predict the surface roughness of AISI 304 steel in terms of machining parameters such as helix angle of cutting tool, spindle speed, feed rate and depth of cut. After milling, the average surface roughness values are measured by using Mitutoyo Surftest SJ201. The predicted model helps us to study the interaction effect of each parameter.

2 Surface Roughness

Irregularities produced on the surface of the specimen by the cutting tool are termed as surface roughness. Surface roughness is characterized by different amplitude parameters, such as average surface roughness (Ra), root-mean-square (rms) roughness (Rq or *R*rms) and maximum peak-to-valley roughness (Rz or *R*max). The average surface roughness (arithmetic mean roughness value or arithmetic average or centre-line average) is the most commonly used parameter to define the surface roughness, and the same is used in this study. The average surface roughness (Ra) is the area between the roughness profile and its mean line, or the integral of the absolute value of the roughness profile height over the evalu-

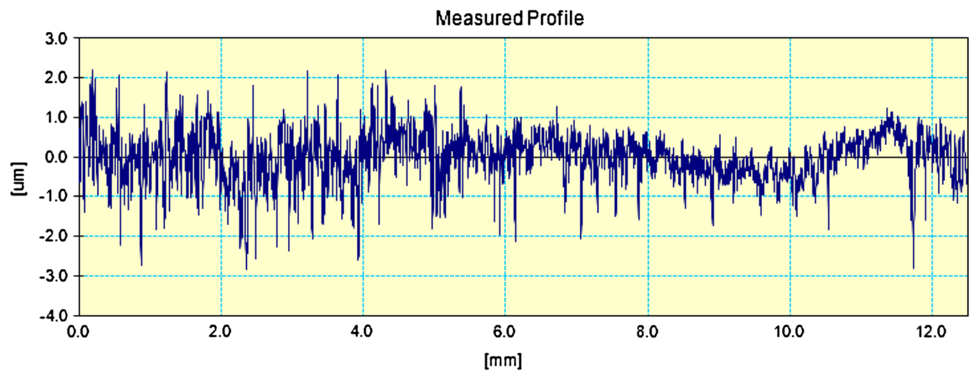


Fig. 1 Measured surface roughness profile for specimen 1

ation length as shown in evaluation length [23]. The average roughness value was measured by using Mitutoyo Surftest SJ201 and the observation are acquired by using Mitutoyo ver 3.0 software, and the profile is traced as shown in Fig. 1.

2.1 Development of Regression Model

In this work, a regression model is developed to predict surface roughness based on experimentally measured values. The coefficients for the regression model are determined using Six Sigma software. The experiment is conducted using design of experiments (DOE).

2.2 Design of Experiments (DOE)

The experiment should provide the required information with minimum time and effort. Therefore, the experimental method and program must be well prepared and designed to conduct experiments. Experimental design is an important tool to aid the experimenter in coping with the complexities of technical investigation.

This is an organized approach to the collection of information. The various steps involved in the design of experiments are given below:

- Identifying the important process control variables
- Finding the upper and the lower limits of the selected control variables
- Development of the design matrix
- Conducting the experiments as per the design matrix
- Evaluation of regression coefficients for the mathematical model
- Development of regression mathematical model.

2.3 Identification of the Process Variables

Specifications of the CNC vertical milling cutter and work piece material used for the experiment are given in Table 1.

Table 1 The technical details of experimental set-up, cutting tool and work piece material

Parameter	Value
Power of spindle motor	5.6 kw
Speed range of spindle motor	0–4,000 rpm
Feed rate (F) m/mm	5.1 m/mm
Torque of spindle and feed motor	45 Nm @ 1,200 rpm
Feed (X & Y dir)	0–450 mm/min
Machine tool	Hass vertical machining centre TM1
Machine weight	1,470 kg
Brand name of cutting tools	Jaiysan cutting tools (ISO Designation P20 grade)
Material of cutter	Uncoated solid carbide end mill
Number of flutes	4
Diameter of cutter	12 mm
Axial rack angle of cutter	18°
Nose radius	0.4 mm
Size of the work piece	32 × 32 × 50 mm
Radial depth of the cut	2.5 mm
Work piece material	AISI 304 austenite stainless steel
Surface roughness measuring instrument and measuring conditions	Mitutoya surf test SJ-201 surf tester and 28 ± 1 °C

Machining conditions set by various process parameters influence the surface roughness which in turn affects the overall quality. The identification of correct process parameters is of paramount importance in obtaining better surface finish. Desired surface roughness may be achieved by properly selecting the independently controllable process variables or factors which influence the surface quality. Among the many independently controllable process parameters affecting surface roughness, helix angle (α), spindle speed (S), feed rate (F) and depth of cut (D) are selected as factors to carry out the experimental works and the development of mathematical models.

Table 2 Parameters and levels in milling

Parameters and notations	Units	Levels				
		−2	−1	0	1	2
Helix angle (α)	Degree (°)	25	30	35	40	45
Spindle speed (S)	Rpm	700	1,400	2,100	2,800	3,500
Feed rate (F)	mm/rev	0.03	0.06	0.09	0.12	0.15
Depth of cut (D)	Mm	0.2	0.4	0.6	0.8	1.0

2.4 Finding the Limits of the Process Variables

The working ranges of all process variables selected had to be determined to fix their levels and to develop the design matrix. This is achieved with the assistance of trial runs carried out by varying one of the process variables while keeping the rest of them at constant value. A large number of trial runs have been conducted for surface roughness at different machining parameters. In conducting the experiment, the upper limit of a factor was coded as +2 and the lower limit as −2, and the coded values for intermediate values were calculated from the following relationship

$$X_i = \frac{2(2X - (X_{\max} + X_{\min}))}{(X_{\max} - X_{\min})} \tag{1}$$

where X_i is the required coded value of a variable X, X is any value of the variable from $X_{\min}$ to $X_{\max}$, $X_{\min}$ is the lower limit of the variable and $X_{\max}$ is the upper limit of the variable. The coded values for intermediate values have been calculated using Eq. (1). The selected process parameters of the experiment for surface roughness, with their limits, units and notations, are given in Table 2.

2.5 Development of Design Matrix

The design matrix chosen to conduct the experiments was a five-level, four-factor central composite rotatable designs consisting of 31 sets of coded conditions and comprising a half replication $2^4 = 16$ factorial design plus 8 star points and 7 centre points. All milling variables at the intermediate level (0) constitute the centre points, while the combination of each milling variables at either its lower level (−2) or its higher level (+2) with the other two variables at the intermediate level constitutes the star points. Thus, the 31 experimental runs allow the estimation of linear, quadratic and two-way interactive effects of the process variables on the surface roughness. The central composite rotatable design matrix is shown in Table 3.

2.6 Conducting the Experiment as Per the Design Matrix for the Measurement of Surface Roughness

Machining experiments have been carried out in a HAAS vertical machining centre as per the design matrix on AISI 304 steel work piece material using an uncoated solid carbide end mill (ISO designation P20 grade, axial rake angle = +18°, nose radius = 0.40 mm) with a diameter of 12 mm and having 4 flutes. The effective rake angle is found to be +18° with reference to Shaw [24]. The work piece is 32 mm wide and 50 mm long and is placed with its longitudinal axis aligned with the direction of feed. The tests have been conducted along a 50 mm edge. The cutting width used in the milling experiment is 2.5 mm. The combination of process parameters in each experimental run and the number of experiments to be conducted corresponds to the design matrix table. The machined surface was measured at three different positions, and the average of three measurements was used as a response value. The surface roughness values (Ra) were taken using a Mitutoya SJ-201 surf tester with a 2.5 mm cut-off value. The HASS vertical CNC machine with AISI 304 steel machining set-up is shown in Fig. 2. The experimental set-up of surface roughness measurement with Mitutoya SJ-201 surf tester is shown in Fig. 3. AISI 304 Steel specimen and solid carbide end mill cutter is shown in Fig. 4.

2.7 Evaluation of Coefficients for Regression Mathematical Model

A procedure based on regression was used for the development of a mathematical model and to predict the surface roughness [25]. The response surface function representing surface roughness can be expressed as Ra $= f(\alpha, S, F, D)$, and the relationship selected is a second-order response surface for k factors is given by Eq. (2).

$$Y = b_o + \sum_{i=1}^{k} b_i X_i + \sum_{\substack{i,j=1 \\ i \neq j}}^{k} b_{ij} X_i X_j + \sum_{i=1}^{K} b_{ii} X_i^2 \tag{2}$$

b_o is the free term of the regression equation. The coefficients b_1, b_2, b_3, b_4 and b_5 are linear terms. The coefficients $b_{11}, b_{22}, b_{33}, b_{44}$ and b_{55} are quadratic terms, and the coefficients $b_{12}, b_{13}, b_{14}, b_{15}, b_{23}, b_{24}, b_{25}, b_{34}, b_{35}$ and b_{45} are interaction terms [26]. The values of the coefficients of the polynomial are calculated by regression with the help of Eq. (3) to Eq. (6).

$$b_o = 0.142857 \left(\sum Y\right) - 0.035714 \sum\sum X_{ii} Y \tag{3}$$

$$b_i = 0.04167 \sum (X_i Y) \tag{4}$$

$$b_{ii} = 0.03125 \sum (X_{ii} Y) + 0.00372 \sum\sum (X_{ii} Y) - 0.035714 \sum Y \tag{5}$$

Table 3 Central composite rotatable design matrix

Machining parameters with coded form					Surface roughness (μm)			% Error	
Exp no	Helix angle α (°)	Spindle speed S (rpm)	Feed rate F (mm/rev)	Depth of cut D (mm)	Measured values	Predicted values using regression	Predicted values using ANN	Using regression model	Using ANN model
1	−1	−1	−1	−1	1.909	1.906	1.9062	0.157	0.146
2	1	−1	−1	−1	1.686	1.68	1.5998	0.356	**0.112**
3	−1	1	−1	−1	1.567	1.538	1.5669	1.851	**0.006**
4	1	1	−1	−1	1.344	1.312	1.341	2.381	**0.223**
5	−1	−1	1	−1	2.058	2.026	2.0591	1.555	−0.053
6	1	−1	1	−1	1.821	1.8	1.816	1.153	**0.274**
7	−1	1	1	−1	1.657	1.658	1.659	−0.060	−0.120
8	1	1	1	−1	1.455	1.432	1.4612	1.581	−0.426
9	−1	−1	−1	1	1.729	1.734	1.7285	−0.289	0.028
10	1	−1	−1	1	1.506	1.508	1.5122	−0.133	−0.411
11	−1	1	−1	1	1.714	1.754	1.7328	−2.334	−1.096
12	1	1	−1	1	1.512	1.528	1.5214	−1.058	−0.621
13	−1	−1	1	1	1.865	1.854	1.8521	0.589	0.491
14	1	−1	1	1	1.596	1.628	1.598	−2.005	−0.125
15	−1	1	1	1	1.922	1.874	1.916	2.497	**0.312**
16	1	1	1	1	1.654	1.648	1.6561	0.363	−0.126
17	−2	0	0	0	2.228	2.249	2.2265	−0.943	0.067
18	2	0	0	0	1.798	1.797	1.7969	**0.056**	0.061
19	0	−2	0	0	1.577	1.577	1.5764	**0.021**	0.038
20	0	2	0	0	1.21	1.229	1.192	−1.570	1.487
21	0	0	−2	0	1.664	1.651	1.6612	0.781	**0.168**
22	0	0	2	0	1.854	1.891	1.8636	−1.996	−0.517
23	0	0	0	−2	1.446	1.501	1.4453	−3.804	0.048
24	0	0	0	2	1.58	1.545	1.5821	2.215	−0.132
25	0	0	0	0	1.536	1.555	1.5283	−1.238	0.501
26	0	0	0	0	1.541	1.555	1.5386	−0.909	0.155
27	0	0	0	0	1.508	1.555	1.5102	−3.117	−0.145
28	0	0	0	0	1.564	1.555	1.5614	0.575	**0.166**
29	0	0	0	0	1.578	1.555	1.5698	1.458	0.519
30	0	0	0	0	1.58	1.555	1.5791	1.582	**0.056**
31	0	0	0	0	1.58	1.555	1.5816	1.582	−0.101

$$b_{ij} = 0.0625 \sum \left(X_{ij} Y\right) \tag{6}$$

Statistical software package DOE PC-IV was used to calculate the values of these coefficients. An initial mathematical model was developed using the coefficients obtained from the above equations. The mathematical model is as follows as shown in Eq. (7).

$$\begin{aligned}\text{Surface roughness (Ra)} &= 1.555 - 0.113\alpha - 0.087S + 0.06F + 0.11D \\ &\quad + 0.117\alpha^2 - 0.038S^2 + 0.054F^2 - 0.08D^2 + 0.004\alpha S \\ &\quad - 0.007\alpha F - 0.005\alpha D + 0.003\mathrm{SF} + 0.097\mathrm{SD} + 0.006\mathrm{FD}\end{aligned} \tag{7}$$

2.8 Testing the Coefficients for Significance

The value of the regression coefficients gives an idea as to what extent the control parameters affect the response quantitatively. The less significant coefficients are eliminated along with the responses with which they are associated without sacrificing much of the accuracy. This is done by using Student's t test [27] and by finding p value. According to this test, when the calculated value of coefficient exceeds the standard tabulated value for the probability criterion kept at 0.75, the coefficient becomes significant and also if the p value of the coefficient is less than 0.05, the coefficient becomes significant; otherwise, it becomes insignificant. The p value of all

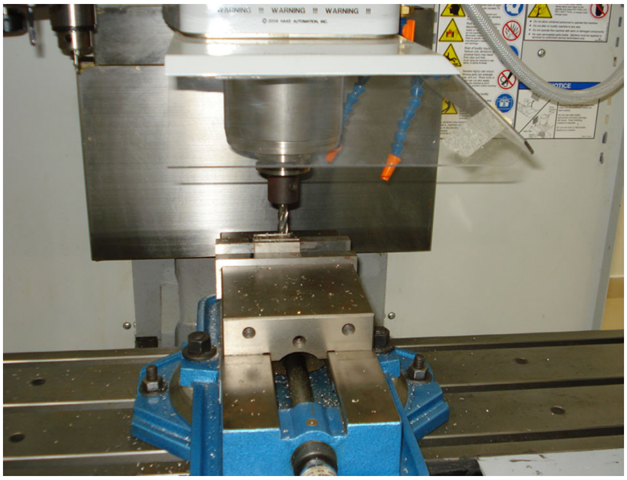


Fig. 2 HASS vertical machining centre with AISI 304 steel specimen

Fig. 3 Surface roughness measurement set-up 2 with Mitutoya SJ-201 surf tester

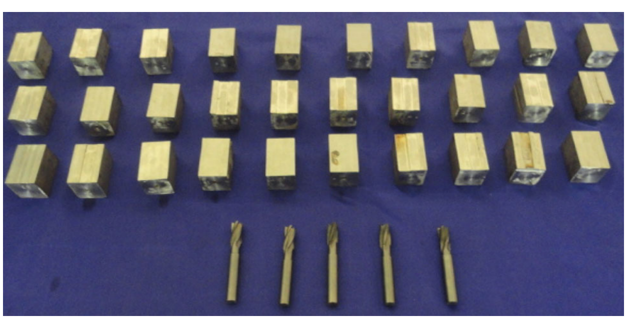


Fig. 4 AISI 304 steel specimen and solid carbide end mill cutter

the coefficients is given in Table 4. The final mathematical model was developed using only the significant coefficients.

From the above table, the coefficients that have p value greater than 0.05 are eliminated. The final mathematical model as determined by the above analysis is given by Eq. (8).

Table 4 P value of coefficients in the mathematical model

S. no	Coefficients in the mathematical model	P-value
1	Constant term	0
2	A	0
3	S	0
4	F	0
5	D	0
6	α^2	0
7	S^2	0
8	F^2	0
9	D^2	0
10	αS	0.681
11	αF	0.452
12	αD	0.580
13	SF	0.767
14	SD	0
15	FD	0.514

$$\text{Surface roughness (Ra)} = 1.555 - 0.113\alpha - 0.087S + 0.06F + 0.11D + 0.117\alpha^2 - 0.038S^2 + 0.054F^2 + 0.08D^2 + 0.097\text{SD} \quad (8)$$

3 The Adequacy of the Developed Model

The adequacy of the model was tested using the analysis of variance techniques (ANOVA). As per the ANOVA technique, it is desired that the calculated value of the F-ratio of the model developed should not exceed the standard tabulated value of the F-ratio for a desired level of confidence (95 %). Also, if the calculated value of the R-ratio of the model developed exceeds the standard tabulated value of the R-ratio for the desired level of confidence (95 %), then the model can be considered to be adequate within the confidence limit. Adequacy of the model was shown in Table 5.

4 Results and Discussion

Based on the mathematical model given in Eq. (7), the effects of various machining parameters on surface roughness (Ra) were studied to analyse the suitable parametric combinations in order to achieve controlled surface roughness. The contour plots were plotted for those parameters which have a significant interaction effect.

4.1 Interaction Effect of Variables

An interaction effect was observed between various process parameters for surface roughness. The most significant inter-

Table 5 Adequacy of the model

Response	Factors df	Lackof Fit df	Pure error	F-ratio		R-ratio		Whether model is adequate
				Model	Standard	Model	Standard	
Surface roughness	9	15	6	1.367	7.56	182.457	7.98	Adequate

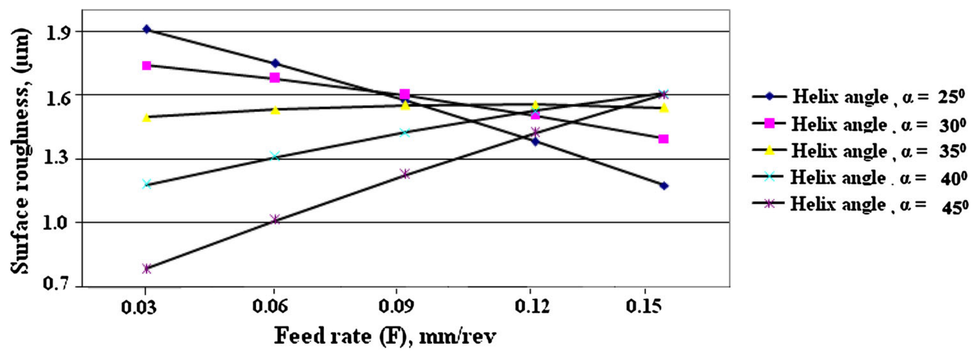


Fig. 5 Interaction effect of helix angle and feed rate on surface roughness

action effect was found between helix angle and feed rate; helix angle and spindle speed; spindle speed and feed rate.

4.2 Interaction Effect of Helix Angle and Feed Rate

The interaction effect of helix angle (α) and feed rate (F) on surface roughness (Ra) is shown in Fig. 5. It reveals that as the helix angle increases, it results in a decrease in surface roughness. The increase in flute angle will reduce the shock load, thus resulting in reduced vibration. It is obvious that when vibration decreases, surface roughness also decreases. For increase in the feed rate value from 0.03 to 0.15 mm/rev surface roughness value decreases for helix angle 25° and 30°, it is moderate at 25° and it increases for helix angle 45° and 45°. These effects are further explained with the help of response surface plots, as shown in Fig. 6. It is evident from the contour surface that Ra is maximum (about 0.192 µm) when α and F are at their higher limits (+2) and is minimum (about 0.78 µm) when α and F are at their lower limits (−2).

4.3 Interaction Effect of Spindle Speed and Feed Rate

The interaction effect of spindle speed (S) and feed rate (F) on surface roughness (Ra) is shown in Fig. 7. From the Fig. 7, it can be observed that as the spindle speed increases, it results in a decrease in surface roughness. By increasing the cutting speed, the surface roughness also decreases. This is because in a certain range of cutting speed, the formation of built-up-edge (BUE) is favoured to decrease the surface roughness [28]. The increase in the feed rate values from 0.03 to0.09 mm/rev decreases surface roughness value; it can be reasoned that increasing the feed rate helps

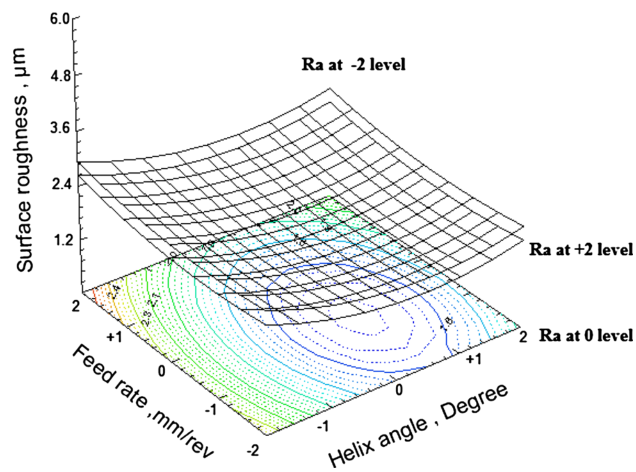


Fig. 6 Contour plot and response surface plot for interaction effect of feed rate and helix angle on surface roughness

to improve surface finish by preventing built edge formation up to 0.09 mm/rev, but increasing further resulted in poor surface finish owing to the increase in chatter vibration. From Fig. 7, it is observed that the surface roughness (Ra) is minimum when the spindle speed is 3,500 rpm and the feed rate ranges from 0.06 to 0.09 mm/rev. These effects are further explained with the help of response surface plots, as shown in Fig. 8. It is evident from the contour surface that Ra is maximum (about 1.93 µm) when S and F are at their higher limits (+2) and is minimum (about 1.23 µm) when α and F are at their lower limits (−2).

4.4 Interaction Effect of Feed Rate and Depth of Cut

The interaction effect of feed rate (F) and depth of cut (D) on surface roughness (Ra) is shown in Fig. 9. From Fig. 9, it

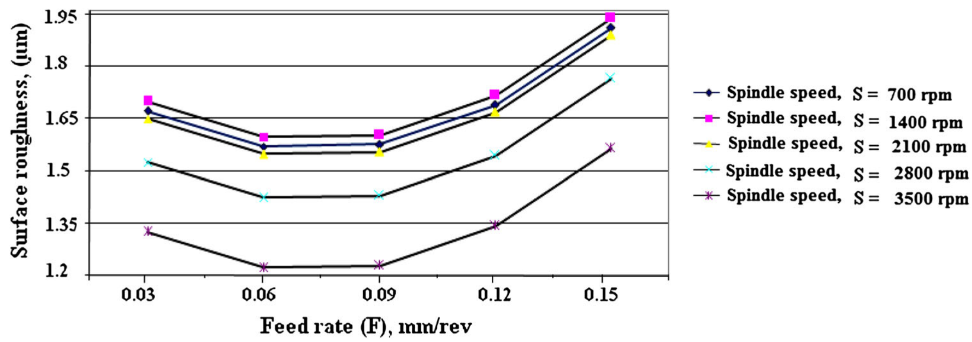


Fig. 7 Interaction effect of spindle speed and feed rate on surface roughness

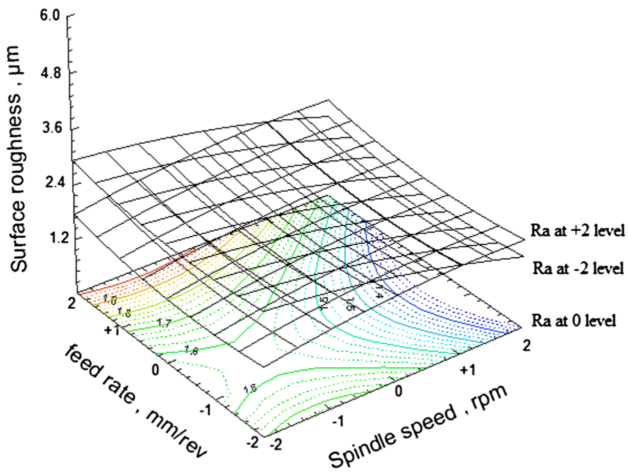


Fig. 8 Contour plot and response surface plot for the interaction effect of feed rate and spindle speed on surface roughness

can be observed that as the feed rate increases from 0.03 to 0.09 mm/rev, it results in a decrease in surface roughness. Further increase in feed rate from 0.09 to 0.15 mm/rev increases the surface roughness value. Also, the increase in depth of cut from 0.2 to 1.0 mm slightly increases the surface roughness. It can be reasoned that an increase in depth of cut renders the end mill cutter and work piece stable, which in turn minimizes chatter vibration. From Fig. 9, it is observed that the surface roughness (Ra) is minimum when the feed rate ranges from 0.06 to 0.09 mm/rev and the depth of cut is 0.2 mm.

5 Development of Neural Network Model

Artificial neural networks, one of the most powerful computer-modelling techniques based on statistical approach, is currently being used in many fields of engineering for modelling complex relationships that are difficult to describe with physical models. The attraction of neural networks comes from their remarkable information, processing characteristics pertinent mainly to nonlinearity, high parallelism, fault and noise tolerance, and learning and generalized capability. There has been continual increase in research interest in the application of artificial neural networks in modelling and monitoring of machining processes. The objective of this study was to model the surface roughness of 304 grade stainless steel specimen.

5.1 Feed-Forward Neural Network Model

The network used here for predicting surface roughness is a feed-forward back-propagation network. The network is a multilayer network. It consists of an input layer used for feeding the input data of the experiment, an output layer used for generating the response and at least one hidden layer used as training function to process the input data and yield output. This network uses network training function that updates weights and bias values, according to the gradient descent to reduce error. Data obtained from the experiments were provided to a network at the learning stage, i.e. machining parameters and surface roughness values. During network

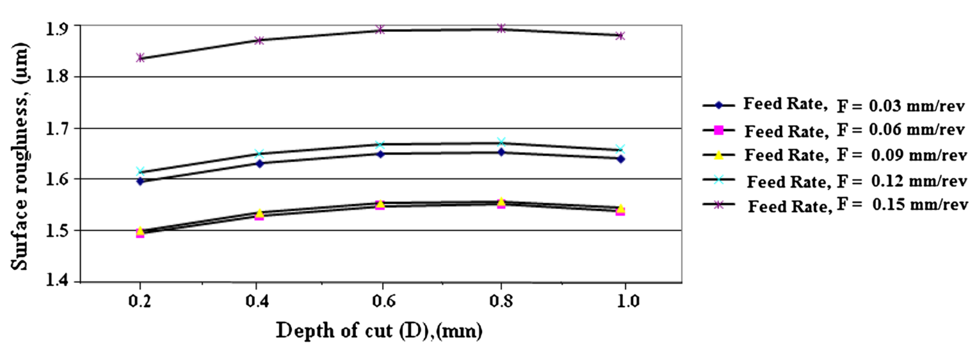
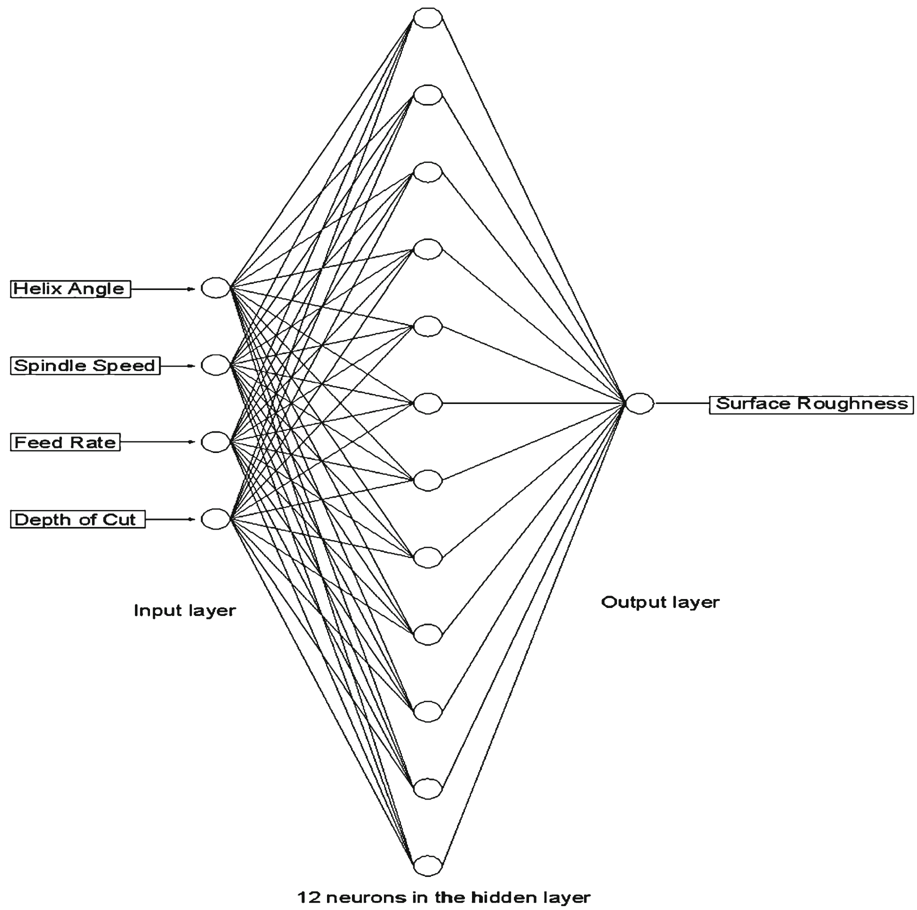


Fig. 9 Interaction effect of feed rate and depth of cut on surface roughness

Fig. 10 Network architecture



learning, the network output was compared with the desired output and the connector weights inside the network were adjusted to minimize the difference. The error was then propagated backwards through the network, and weights were changed, based on the feed-forward back-propagation learning algorithm. This learning process is an iterative one and was stopped once an acceptable error was reached. When the trained network was presented with new input (beyond training), the network responded according to the knowledge it acquired [28,29].

5.2 Training the Neural Network

In this study, the input parameters used were the four main parameters, i.e. helix angle (α), spindle speed (S), feed rate (F) and depth of cut (D). The output parameter was the response, i.e. surface roughness. In total, 31 experimental data were collected for building the neural network model. In order to relieve the training difficulty and balance the importance during the training process, the data should be normalized. The data are normalized between slightly offset values such as 0.1 and 0.9 rather than between 0 and 1 to avoid saturation of the sigmoid function leading to slow or no learning. The normalized values for each row of input and output data set were calculated using Eq. (4) [30]

$$X_i = 0.1 + 0.8\left(\frac{Z_i - Z_{\min}}{Z_{\max} - Z_{\min}}\right) \tag{9}$$

where X_i normalized input/output value, Z_i actual input/output value, $Z_{\max}$ maximum input/output value and $Z_{\min}$ minimum input/output value.

A feed-forward back-propagation artificial neural network model was created keeping four neurons in the input layer, one neuron in the hidden layer and one neuron in the output layer by using MATLAB 7.6 [31]. The number of neurons in the hidden layer varied between 1 and 25, and they had to be decided based on trial and error. This was determined by gradually increasing the number of neurons and observing their effect on the predicted value. Finally, the structure of the network selected was 4–12–1 (4 neurons in the input layer, 12 neurons in the hidden layer and 1 neuron in the output layer). The network architecture is shown in Fig. 10. There is no specific rule available on how many data could be used for training and how much for testing and validation. The general guide line is that the training data should be more than testing and validation. Hence, out of 31 experimental data,

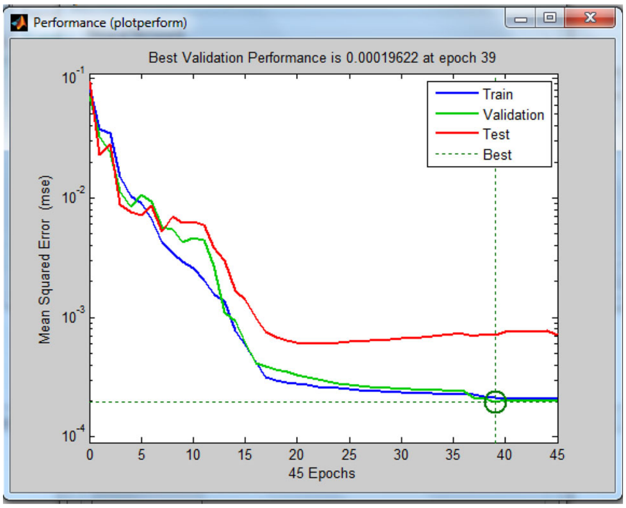


Fig. 11 Performance goal of the network

70 % was used for training, 15 % for testing and another 15 % for validation. Thus, in total, 21 data were used for training, 5 data for testing and 5 data for validation.

6 Testing the Neural Network

The network was trained to determine the performance of the established model of surface roughness. During training, each time a set of inputs X_i of a training sample was presented and the corresponding output Y_o (predicted values) was obtained. The predicted value of the network model was compared with the actual value (Y_d). The comparison was done by calculating the mean sum of the squared error (MSE) between Y_d and Y_o using Eq. (5)

$$\mathrm{MSE} = (Y_d - Y_o)^2 \tag{10}$$

The objective of the algorithm is to minimize the mean sum of squared error for the entire experimental data. In this study, the network was trained for 45 iterations. Further training did not seen to improve the modelling performance of the network. The average MSE obtained was 0.00019622, which shows that the model is very accurate. The performance goal of the network is displayed in Fig. 11.

6.1 Validity of the Neural Model

The validity of the neural model was tested by conducting additional tests, as shown in Table 6. From the above table, it can be inferred that the error percentage for additional tests falls within the range of 0.0457 to −1.631 %. Hence, the above model can be effectively used for predicting surface roughness.

From the conformity test, it was found that the developed ANN model is able to predict surface roughness with a reasonable accuracy.

6.2 Comparison of Regression and ANN Models

The regression and ANN models are compared with error percentage. The average error percentage of regression model is above 2 %. But in most cases, the error percentage of ANN model is found to be less than 2 %. The predictions of neural network model are accurate and reliable than regression model.

7 Conclusions and Future Scope

This investigation presented a regression and artificial neural network model to predict surface roughness in terms of helix angle, spindle speed, feed rate and depth of cut. The helix angle is the one of the significant parameter to reduce the surface roughness. Increasing the helix angle decreases the surface roughness. Increase in feed rate, depth of cut and spindle speed increases the surface roughness. The interactions between the process parameter were analysed. Artificial neural network was developed to predict surface roughness. The error in the surface roughness values predicted by using regression model and neural network model compared with experimentally measured value was found to be less than

Table 6 Confirmatory tests for validity of neural model

Trial no.	Machining parameters in coded values				Surface roughness (µm)		Percentage error
	α (°)	S (rpm)	F (mm/rev)	D (mm)	Observed values	Predicted values	
01	2	2	2	2	2.186	2.185	0.0457
02	1	1	1.5	1	1.741	1.7455	−0.2585
03	0	1.5	−1	1.5	1.529	1.54975	−1.357
04	−1	−2	0	0.5	1.686	1.7135	−1.631
05	2	−1	−0.5	−0.5	1.853	1.8705	−0.944
06	0	0.5	1	1.5	1.602	1.637	−1.321

5 %. The predictions of neural network model are accurate and reliable than regression model as in most cases the error percentage is found to be less than 2 %. Hence, it can be concluded that the developed models possess promising potential in the application of predicting surface roughness in end milling operations. Further study could consider more factors (different tool geometry, coating type, materials, cutting conditions, lubricant, cooling strategy etc.) in the study to see how these factors could affect the surface roughness.

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