

## Response surface and artificial neural network prediction model and optimization for surface roughness in machining

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### ABSTRACT

The present paper deals with the development of prediction model using response surface methodology and artificial neural network and optimizes the process parameter using 3D surface plot. The experiment has been conducted using coated carbide insert in machining AISI 1040 steel under dry environment. The coefficient of determination value for RSM model is found to be high ( $R^2 = 0.99$  close to unity). It indicates the goodness of fit for the model and high significance of the model. The percentage of error for RSM model is found to be only from -2.63 to 2.47. The maximum error between ANN model and experimental lies between -1.27 and 0.02 %, which is significantly less than the RSM model. Hence, both the proposed RSM and ANN prediction model sufficiently predict the surface roughness, accurately. However, ANN prediction model seems to be better compared with RSM model. From the 3D surface plots, the optimal parametric combination for the lowest surface roughness is d1-f1-v3 i.e. depth of cut of 0.1 mm, feed of 0.04 mm/rev and cutting speed of 260 m/min respectively.

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## 1. Introduction

Machining is a chip removal process in which less utility and less value raw materials are converted into high utility and valued products with definite dimensions, forms and finish, which satisfies some function. Solid-state manufacturing processes can be broadly classified in to metal forming and metal machining. During metal forming, the volume is conserved and shape is achieved through deforming the material plastically in processes like forging, rolling, drawing etc. However, these mostly serve as primary or basic operations for typical products. In around eighty percent of components produced through metal forming, machining is essentially required to achieve dimensional accuracy, form accuracy and good surface finish to achieve the functional requirements.

Keeping an eye to achieve higher productivity and good surface finish, research in the field of cutting tool materials have been taken place in recent years. The ease with which a work material can be machined is referred to as Machinability. It directly influences the effectiveness, efficiency and overall economy of the machining process. Surface quality has received serious attention for many years. It has

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formed an important design feature in demanding situations arising of fatigue loads, precision fits, corrosion resistance and aesthetic requirements. The surface quality is affected by the process parameters, machine tool condition, cutting tool geometry and condition and the machining operations. Therefore, research in the field of surface quality in machining is highly essential for functional requirements of the products. The surface roughness prediction model and optimization of process parameters is especially important for achieving better surface quality in machining. Therefore, the present paper deals with these aspects in details.

## 2. Review of literature

Gökkaya and Nalbant (2007a) observed that lower surface roughness was induced using a CVD multi layer coated tool outermost with TiN compared to uncoated, coated with AlTiN and coated with TiAlN using the PVD technique during dry turning of AISI 1015 steel. Tıgıt et al. (2009) compared the wear behavior of multilayer-coated carbide tools (TiCN+TiC+Al<sub>2</sub>O<sub>3</sub>+TiN) with different coating thickness of 7.5µm and 10.5µm to uncoated carbide tool. Multilayer TiN coated carbide tool with 10.5µm thickness performed better than uncoated carbide insert with respect to surface quality and cutting forces in machining spheroidal graphite cast iron in all cutting speeds. This indicated economical machining with respect to cutting energy and power consumptions.

Gillibrand et al. (1996) studied the economic benefit of finish turning with coated carbide and uncoated carbide cutting tool. It was observed that the machining cost using coated carbide is 30% less than uncoated carbide during finish turning of medium carbon steel. The surface roughness was low using TiN coated carbide tools and an improvement in tool life between 250 and 300% compared to uncoated carbide tools are achieved. Noordin et al. (2001) compared the performance of coated and uncoated carbide inserts during finish turning of AISI1010 steel. The tool of (CVD TiCN/TiC and PVD with TiN) performed better than CVD with (TiCN/TiC/Al<sub>2</sub>O<sub>3</sub>) and uncoated carbide insert as lower forces and surface roughness obtained and chips with minimum thickness produced that contributed to low chip strain and low residual stresses on the workpiece surface.

Che Haron et al. (2007) reported that the surface roughness for uncoated carbide tools was in the range of 0.36-4.05 µm and 0.30-1.51µm for coated carbide insert (CVD TiN/ Al<sub>2</sub>O<sub>3</sub>/TiCN) respectively during turning AISI D2 (22 HRC) steel. The lowest surface roughness value for both types of carbide tools were observed at cutting speed of 250 m/min and feed rate of 0.05 mm/rev. Gökkaya and Nalbant (2007b) investigated the effects of different insert radii, depths of cut and feed rates on the surface quality of the work pieces during machining of AISI 1030 steel without coolant by CVD multilayer coated carbide [TiC/Al<sub>2</sub>O<sub>3</sub>/TiN (outermost is TiN)] insert. It was observed that increase of insert radius decreases the surface roughness and increasing cutting speed and depth of cut increases the surface roughness.

Nalbant et al. (2007) found that, greater insert radius; low feed rate and low depth of cut could be recommended to obtain better surface roughness in turning AISI 1030 steel with TiN coated carbide insert. The experiment was performed utilizing Taguchi L<sub>9</sub> orthogonal array. Noordin et al. (2004) described the performance of a multilayer coated WC tool (TiCN/Al<sub>2</sub>O<sub>3</sub>/TiN) of CNMG120408-FN and TNMG120408-FN type during turning AISI 1045 steel (187 BHN) based on central composite design and response surface methodology (RSM). The feed was the most significant factor for surface roughness and the tangential force.

Risbood et al. (2003) found that, using neural network, surface finish could be predicted within a reasonable degree of accuracy in turning with TiN coated tools. Suresh et al., (2002) developed a surface roughness prediction model for machining mild steel using RSM with TiN-coated WC cutting tools. It was found that, the surface roughness was decreased with an increase in cutting speed and increased as feed elevated. An increase in depth of cut and nose radius increased the surface roughness. The optimal machining condition was obtained by genetic algorithm (GA) approach.

Dabnun et al. (2005) developed response model (surface roughness) utilizing factorial DOE and response surface methodology during machinability studies of glass ceramic using uncoated carbide inserts under dry cutting conditions. Feed rate was the main influencing factor on the roughness, followed by the cutting speed and depth of cut. Feng (2001) applied fractional factorial design approach to study the influence of turning parameters on surface roughness using multilayer coated carbide inserts (TiCN/Al<sub>2</sub>O<sub>3</sub>/TiN). Feed, nose radius, work material and speeds, the tool point angle were found to be the influencing parameters on surface roughness.

Most dominant interactions were found between work materials, point angle and speeds. The depth of cut was found to insignificant for surface roughness. Nalbant et al. (2007) developed predictive neural network model and found better predictions than various regression models for surface roughness in machining AISI 1030 steel using coated carbide tool (TiC/ Al<sub>2</sub>O<sub>3</sub>/TiN). Feed rate and insert nose radius were main influencing factors on the surface roughness. Depth of cut was not more informative than the other two. Sahoo and Sahoo (2011) developed RSM model for surface roughness and optimize the process parameter in machining D2 steel using TiN coated carbide insert. The developed RSM model sufficiently predicts the surface roughness in turning D2 steel.

Sahoo et al. (2013) presents the development of flank wear model in turning hardened EN 24 steel with PVD TiN coated mixed ceramic insert under dry environment. The paper also investigates the effect of process parameter on flank wear (VBc). The experiments have been conducted using three level full factorial design techniques. The machinability model has been developed in terms of cutting speed ( $v$ ), feed ( $f$ ) and machining time ( $t$ ) as input variable using response surface methodology. The adequacy of model has been checked using correlation coefficients.

Quiza et al. (2008) performed experiment on hard machining of D2 steel (60 HRC) using ceramic cutting tools. Neural network model was found to be better predictions of tool wear than regression model. Park (2002) observed that PCBN cutting insert performed better in cutting force and surface roughness than ceramic tool in turning hardened steel. Feed rate was found to be significant on surface roughness while the effect of the cutting speed and depth of cut was negligible. The optimal cutting conditions for the best surface quality were selected by using Taguchi orthogonal array concept.

Ozel et al. (2007) found that neural network model was suitable to predict tool wear and surface roughness patterns for a range of cutting conditions in finish hard turning of AISI D2 steels (60 HRC) using ceramic wiper (multi-radii) design inserts. Lalwani et al. (2008) studied the effect of cutting parameters on cutting forces and surface roughness in finish hard turning using coated ceramic tool applying RSM and sequential approach using face centered CCD. A linear model fitted well to the variation of cutting forces and a non-linear quadratic model found suitable for the variation of surface roughness with significant contribution of feed rate. Depth of cut was significant to the feed force. For the thrust force and cutting force, feed rate and depth of cut contributed more.

Horng et al. (2008) developed RSM model using CCD in the hard turning using uncoated Al<sub>2</sub>O<sub>3</sub>/TiC mixed ceramics tool for flank wear and surface roughness. Flank wear was influenced principally by the cutting speed and the interaction effect of feed rate with nose radius of tool. The cutting speed and the tool corner radius affected surface roughness significantly. Sahin and Motorcu (2008) indicated that the feed rate was found out to be dominant factor on the surface roughness, but it decreased with decreasing cutting speed, feed rate, and depth of cut in turning AISI 1050 hardened steels by CBN cutting tool. The RSM predicted and experimental surface roughness values were found to be very close. Sahoo and Mohanty (2013) obtained the optimal values of cutting speed, feed and depth of cut to minimize cutting force and chip reduction coefficient during orthogonal turning using Taguchi quality loss function. The effectiveness of the proposed methodology is illustrated through an experimental investigation in turning mild steel workpiece using high speed steel tool. Sahoo (2014) studied the performance of multilayer coated carbide insert in the machining of hardened AISI D2 steel (53 HRC) using Taguchi design of experiment. Based on Taguchi S/N ratio and ANOVA, feed is the

most influencing parameter for surface roughness followed by cutting speed whereas depth of cut has least significant from the experiments. In regression model, the value of  $R^2$  being 0.98 indicates that 98 % of the total variations are explained by the model. It indicates that the developed model can be effectively used to predict the surface roughness on the machining of D2 steel with 95% confidence intervals. Pal and Chakraborty (2005) developed a back propagation neural network model for the prediction of surface roughness in turning operation of mild steel workpiece using high speed steel as the cutting tool. The performance of the trained neural network was tested with experimental data, and found to be in good agreement. Tsao and Hocheng (2008) predicted and evaluated thrust force and surface roughness in drilling of composite material using Taguchi method and the artificial neural network. A correlation was established between the feed rate, spindle speed and drill diameter. The correlations were obtained by multi-variable regression analysis and radial basis function network (RBFN) and compared with the experimental results. The results indicated the RBFN is more effective than multi-variable regression analysis.

Davim et al. (2008) developed surface roughness prediction models using artificial neural network (ANN) during turning of free machining steel and reported that the cutting speed and feed rate had significant effects in reducing the surface roughness, while the depth of cut has the least effect. Sharma et al. (2008) constructed neural network models for cutting forces and surface roughness for different cutting parameters such as approach angle, speed, feed and depth of cut. Surface roughness ( $R_a$ ) was positively influenced with feed and a negative trend was observed with approaching angle, speed and depth of cut. The neural network model for  $R_a$  predicted with moderate accuracy. Cutting force ( $F_c$ ) increased with the increase in approach angle, feed and depth of cut where as it decreased with speed. Passive force ( $F_p$ ) increased with increase in depth of cut, speed and feed where as it decreased with increase in approaching angle. Feed force ( $F_f$ ) increased with all variables, i.e. approaching angle, speed, feed and depth of cut. The neural network model for cutting force ( $F_c$ ) predicted with high accuracy and for cutting force  $F_p$  predicted with moderate accuracy.

Ozel and Karpat (2005) predicted surface roughness and tool flank wear over the machining time through neural network modeling for variety of cutting conditions in finish turning of hardened AISI H-13 steel. It was observed that surface roughness reduced with the decrease in the feed rate, but the tool wear development was slightly faster. Also, it was observed that on increasing cutting speed, there was a significant increase in tool wear development but better surface finish was obtained. Bagci and Isik (2006) developed artificial neural network (ANN) and response surface (RS) model to predict the surface roughness on the turned part surfaces of unidirectional glassfibre reinforced plastics (GFRP), using cermet tools. They observed good agreement between the predictive model results and the experimental measurements.

Karayel (2009) presented a feed forward multilayered neural network for the prediction and control of surface roughness values for different turning conditions of st 50.2 steel, using a CNC lathe. It was observed that the feed rate was the dominant parameter for surface roughness and it increased rapidly with the increase in feed rate. The cutting speed had a critical value for which the best surface quality can be achieved. The effect of depth of cut on surface roughness was not regular and had a variable character. ANN produced an accurate relationship between cutting parameters and surface roughness. Sehgal and Meenu (2013) observed that the artificial neural network (ANN) model predicts with higher accuracy than response surface methodology (RSM) in context to surface roughness in end milling of Ductile Iron grade 80-55-06. TANSIG training transfer function along with PURELIN output transfer function is observed to be the most appropriate training transfer function.

Research in the field of surface quality in machining is highly essential for functional requirements of the products. Thus, the objective of the present work has been set to have a study to evaluate the performance of coated carbide tools under varying parameter of machining. The predictive model using response surface methodology (RSM) has been developed for surface roughness in machining AISI

1040 steel under dry environment. Next, the optimal parametric combination of process parameter has been obtained from 3D surface plot using RSM.

### 3. Experimental details

Over the last few years, coated carbide tools have been widely used; became popular and it is preferred to uncoated carbide tools in machining steels. For experimental investigations, commercially available PVD TiAlN coated carbide insert designated as CNMG 120408 EN-M52 was used and performed under dry environment. The 80° diamond-shaped insert is one of the popular inserts used with negative side cutting edge angle. AISI 1040 steel rods of 25 mm diameter and 75 mm length were turned on a high rigid lathe (HMT, NH-22, India). The cutting insert has the following specification: coating thickness 2-5  $\mu\text{m}$ , grain size 1 $\mu\text{m}$ , hardness 1560HV and nose radius of 0.8 mm. The insert is mounted on a tool holder designated by ISO PCLNR2525M12 with cutting geometry as follows: clearance angle ( $\alpha_o$ ) = 6°, negative rake angle ( $\gamma_o$ ) = -6°, negative cutting edge inclination angle ( $\lambda$ ) = -6° and major cutting edge angle or approach angle = 95°, point angle = 80° and nose radius ( $r$ ) = 0.8mm. The test specimen AISI 1040 is widely used for bolts for machines, plows, and carriages; cylinder head stubs, U-bolts, concrete reinforcing rods, and springs.

**Table 1**

Process parameters and their levels

Parameters	Notation	Unit	Levels of parameters		
			Level 1	Level 2	Level 3
Cutting speed	v	m/min	60	160	260
Feed	f	mm/rev	0.04	0.08	0.12
Depth of cut	d	mm	0.1	0.3	0.5

**Table 2**

Experimental observations

Run	Setting value			Average Ra ( $\mu\text{m}$ )
	v	f	d	
1	60	0.04	0.1	1.40
2	60	0.04	0.3	1.57
3	60	0.04	0.5	1.75
4	60	0.08	0.1	1.80
5	60	0.08	0.3	1.98
6	60	0.08	0.5	2.10
7	60	0.12	0.1	2.30
8	60	0.12	0.3	2.35
9	60	0.12	0.5	2.42
10	160	0.04	0.1	1.44
11	160	0.04	0.3	1.61
12	160	0.04	0.5	1.65
13	160	0.08	0.1	1.85
14	160	0.08	0.3	1.89
15	160	0.08	0.5	1.92
16	160	0.12	0.1	2.23
17	160	0.12	0.3	2.28
18	160	0.12	0.5	2.33
19	260	0.04	0.1	1.46
20	260	0.04	0.3	1.52
21	260	0.04	0.5	1.55
22	260	0.08	0.1	1.73
23	260	0.08	0.3	1.78
24	260	0.08	0.5	1.81
25	260	0.12	0.1	2.05
26	260	0.12	0.3	2.18
27	260	0.12	0.5	2.10

The arithmetic surface roughness average (Ra) of workpiece material is considered as the performance measuring criteria. The process parameters and their levels are shown in Table 1 (cutting speed in the range of 60-260 m/min, feed of 0.04-0.12 mm/rev and depth of cut of 0.1-0.5 mm respectively). The measurements of surface roughness were performed by a surface roughness tester (Taylor Hobson, Surtronic 25) with 0.8 mm sampling length and 4mm traversing length respectively. The measurements were repeated three times at different locations and average value was reported. The average surface roughness (Ra) was used to evaluate the surface roughness of machined surface. Experimental design by full factorial design (FFD) with three factors and three levels involves 27 numbers of experiments. The experimental results have been shown in Table 2.

## 4. Results and discussions

### 4.1. Prediction model (RSM and ANN)

Taking surface roughness as output and process parameters (cutting speed, feed and depth of cut) as input, the prediction model using response surface methodology (RSM) has been developed at 95% confidence level. Response surface methodology is a collection of mathematical and statistical techniques that are useful for the modeling and analysis of problems in which output or response is influenced by several input variables and the objective is to find the correlation between the response and the variables investigated (Montgomery, 1997). Using least square fitting, the model is developed. The experiments are conducted based on full factorial design, which gives a comparatively accurate prediction of surface roughness average. The first step of RSM is to find a suitable approximation for the true functional relationship between surface roughness and set of independent variables utilized. In the linear model, the surface roughness is well modeled by linear function. However, in the second order model like response surface methodology, there is a curvature in the system. The second order response surface representing the surface roughness (Ra,  $\mu\text{m}$ ) can be expressed as a function of three process parameters such as v, f and d. It has been expressed applying regression analysis using least square method. The following second order equation for quality characteristics is obtained.

$$Ra = 0.8498 + 0.0018 v + 9.1458 f + 1.4222 d - 0.0000 v^2 + 16.3194 f^2 - 0.5972 d^2 - 0.0115 vf - 0.0023 vd - 3.9583 fd$$

$$(R^2 = 99.2 \%, R^2 (\text{adj}) = 98.8 \%) \quad (1)$$

This analysis is carried out for a level of significance of 5%, i.e., for a level of confidence of 95%. For model adequacy checking, the residual plots are examined for a regression model with designed experiment. The normal probability plot should not show violations of the normality assumption. In the ANOVA (Table 3) of response surface model, analyzing of variance shows that the terms having the values of probability less than 0.05 are significant. Using uncoded units, models are developed. From the RSM model, it is evident that the regression is significant. In addition, regression, linear, square and interaction terms from the RSM model are significant because P value is less than 0.05.

**Table 3**

Results of ANOVA for Ra 2<sup>nd</sup> order model.

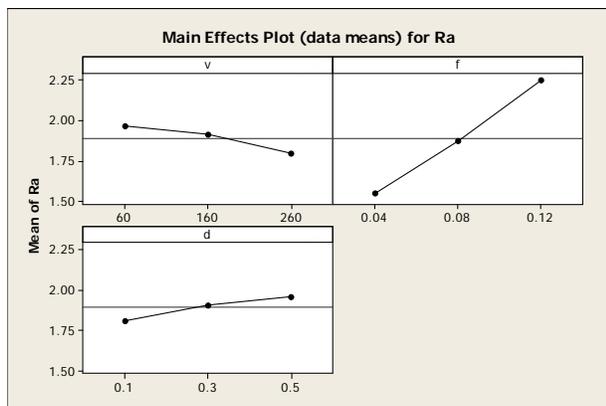
Source	DF	Seq SS	Adj SS	Adj MS	F	P value	Remarks
Regression	9	2.5011	2.5011	0.2779	243.51	0.000	Significant
Linear	3	2.4256	0.0807	0.0269	23.59	0.000	Significant
Square	3	0.0131	0.0131	0.0043	3.83	0.029	Significant
Interaction	3	0.0624	0.0624	0.0208	18.24	0.000	Significant
Residual Error	17	0.0194	0.0194	0.0011			
Total	26	2.5205					

The main effect of feed was found to be the most significant factor. Each level of the factors affects the response differently. From ANOVA Table 4, main effect plot (Fig. 1) and interaction plot (Fig.2), it is evident that, feed is the significant factor affecting surface roughness followed by cutting speed and

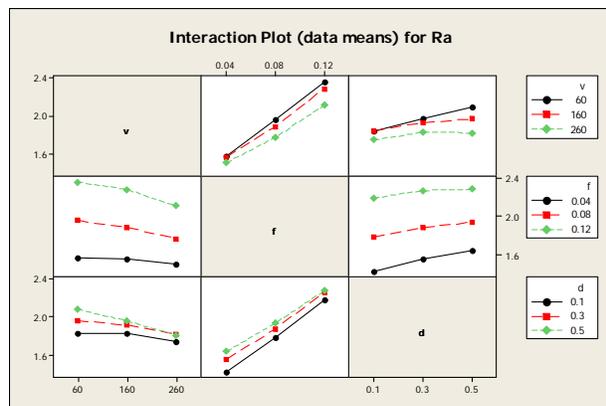
depth of cut. From interaction plot, all the interaction terms are significant. Also from the Eq. (1), it is seen that the RSM model has high determination coefficient ( $R^2 = 0.99$  close to unity). It describes 99% of the variability in the response. It indicates the goodness of fit for the model and high significance of the model. In addition, the adjusted  $R^2$  value is very close to the predicted  $R^2$ . Therefore, the predicted  $R^2$  is in reasonable agreement with the adjusted  $R^2$ . It is evident that the unnecessary terms are not added in the model. This analysis showed that the prediction model sufficiently explains the relationship between surface roughness and the independent variables.

**Table 4**  
ANOVA for Ra

Source	DF	SS	MS	F	P value	Remarks
v	2	0.1289	0.0644	15.75	0.000	Significant
f	2	2.2021	1.101	269.03	0.000	Significant
d	2	0.1077	0.0538	13.16	0.000	Significant
Error	20	0.0818	0.004			
Total	26	2.5205				

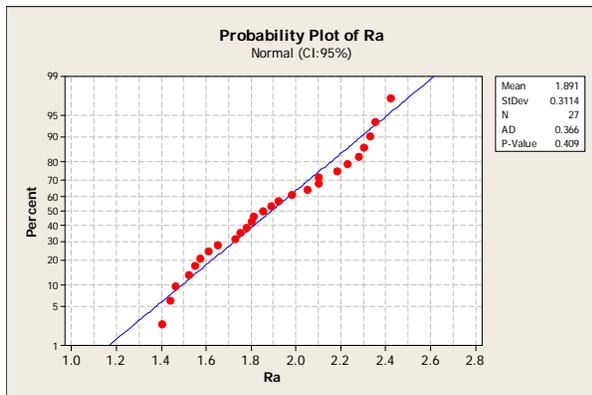


**Fig.1.** Main effect plot for Ra

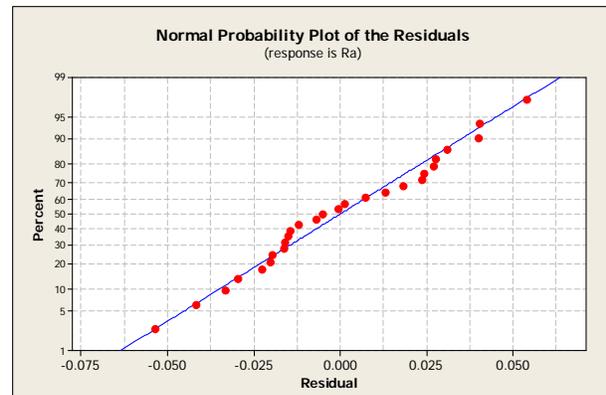


**Fig. 2.** Interaction plot for Ra

The data closely follows the straight line, which is observed from the Anderson-Darling tests (Fig. 3). Since the P value is greater than 0.05 (at 95 % confidence level), it signifies that the data follows a normal distribution and the model developed by Eq. (1) is suitable and quite adequate. The normal probability plot (Fig. 4) gives the information about the residuals, which is close to the straight line. It indicates that the errors are distributed normally and proposed model is significant.

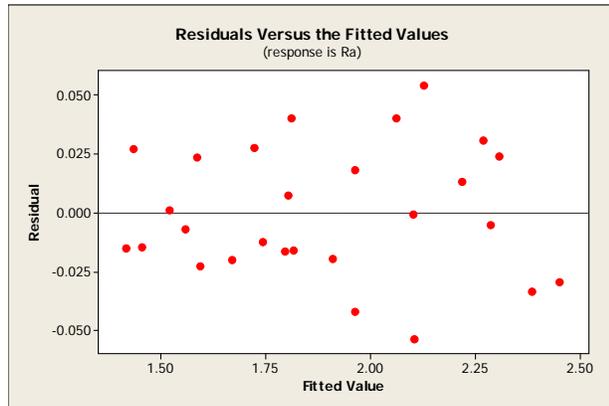


**Fig. 3.** Anderson Darling test of normality for Ra

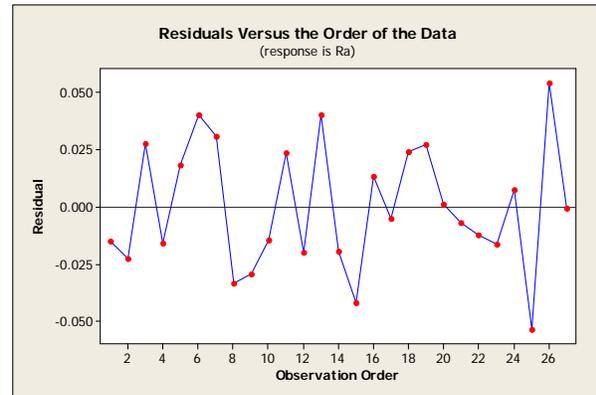


**Fig. 4.** Normal probability plot of the residuals for Ra

The graph of residuals vs. fitted values is shown in Fig. 5. No unusual structure is apparent except one point that is much larger or smaller than the others are. As its standardized residual is within the range of -3 to 3, the model proposed is significant. The graph of residual vs. order of data (Fig. 6) shows the residual for the run order of experiment. This implies that the residuals are random in nature and do not exhibit any pattern with run order. In addition, figure of residual vs. order of data revealed that there is no noticeable pattern or unusual structure present in the data.



**Fig. 5.** Residuals vs. fitted value for Ra



**Fig. 6.** Residuals vs. order of the data for Ra

Another predictive model based on ANN (Artificial neural network) is employed, and the experimental results are compared with it and also with RSM model. The neural network is constructed using the experimental database. About 80% of data are used for training, whereas 20% of data are used for testing of the model. The selected and optimized parameters for training of the ANN model have been presented in Table 5.

A comparison of experimental results with RSM and ANN results for surface roughness is presented in Table 6. It is observed that the maximum error between ANN model and experimental lies between -1.27 to 0.02 %, which is significantly less than the RSM model. However, this error can be further reduced if the number of test patterns will be increased. Hence, the developed ANN model can be effectively utilized for prediction of surface roughness in machining. The percentage of error for RSM model is found to be only -2.63 to 2.47. Hence, both the proposed RSM and ANN prediction model sufficiently predicts the surface roughness accurately. However, ANN prediction model is found to be better compared to RSM model.

**Table 5**

Input parameters selected for training

Input Parameters for Training	Values
Error tolerance	0.001
Learning rate ( $\beta$ )	0.2
Momentum parameter( $\alpha$ )	0.01
Noise factor (NF)	0.001
Number of epochs	10,00,000
Slope parameter ( $\xi$ )	0.6
Number of hidden layer neuron (H)	7
Number of input layer neuron (I)	3
Number of output layer neuron (O)	1

**Table 6**

Comparisons of experimental vs. RSM and ANN for surface roughness

Run	Average Ra ( $\mu\text{m}$ ) (Experimental)	Predicted (RSM)	Residuals (RSM)	% of error (RSM)	Predicted (ANN)	Residuals (ANN)	% of error (ANN)
1	1.40	1.41	-0.015	-1.07	1.41	-0.01	-0.71
2	1.57	1.593	-0.023	-1.46	1.59	-0.02	-1.27
3	1.75	1.722	0.028	1.6	1.72	0.03	0.01
4	1.80	1.816	-0.016	-0.88	1.80	0.00	0.00
5	1.98	1.962	0.018	0.9	1.97	0.010	0.005
6	2.10	2.06	0.04	1.9	2.07	0.03	0.01
7	2.30	2.269	0.031	1.34	2.25	0.05	0.02
8	2.35	2.383	-0.033	-1.4	2.39	-0.04	-0.01
9	2.42	2.45	-0.03	-1.23	2.44	-0.02	-0.008
10	1.44	1.455	-0.015	-1.04	1.45	-0.01	-0.006
11	1.61	1.586	0.024	1.49	1.58	0.03	0.01
12	1.65	1.67	-0.02	-1.21	1.66	-0.01	-0.006
13	1.85	1.81	0.04	2.16	1.82	0.03	0.01
14	1.89	1.91	-0.02	-1.05	1.91	-0.02	-0.01
15	1.92	1.962	-0.042	-2.18	1.96	-0.04	-0.02
16	2.23	2.217	0.013	0.58	2.22	0.01	0.004
17	2.28	2.285	-0.005	-0.21	2.28	0.00	0.00
18	2.33	2.306	0.024	1.03	2.29	0.04	0.01
19	1.46	1.433	0.027	1.84	1.43	0.03	0.02
20	1.52	1.519	0.001	0.06	1.50	0.02	0.01
21	1.55	1.557	-0.007	-0.45	1.55	0.00	0.00
22	1.73	1.742	-0.012	-0.69	1.75	-0.02	-0.01
23	1.78	1.796	-0.016	-0.89	1.79	-0.01	-0.005
24	1.81	1.803	0.007	0.38	1.81	0.00	0.00
25	2.05	2.104	-0.054	-2.63	2.09	-0.04	-0.01
26	2.18	2.126	0.054	2.47	2.14	0.04	0.01
27	2.10	2.101	-0.001	-0.04	2.10	0.00	0.00

## 4.2. Optimization

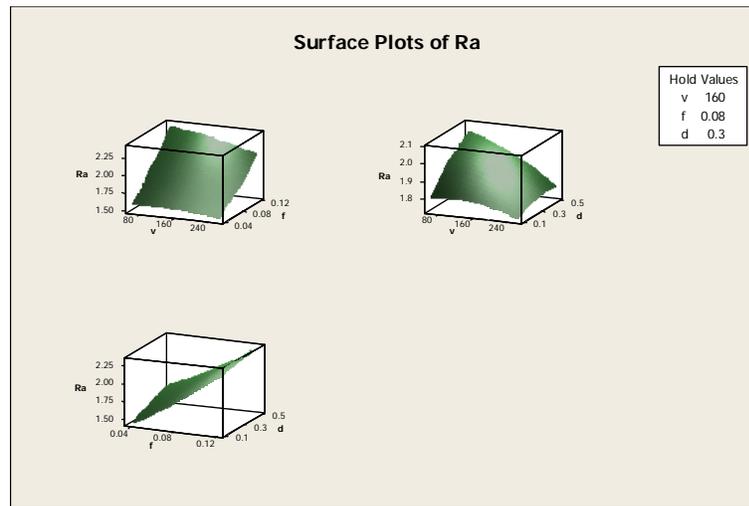
The response surface plot can help in the prediction of the surface roughness at any zone of the experimental domain. The surface plot (Fig. 7) is as follows:

$f^*d$ : This plot indicates that how variables, feed and depth of cut are related to the surface roughness while the cutting speed is held at constant at middle level. The response is at its lowest at the lightest region of the surface plot ( $f = 0.04$  mm/rev and  $d = 0.1$  mm).

$v^*d$ : This plot indicates that how variables, cutting speed and depth of cut are related to the surface roughness while the feed is held at constant at middle level. The response is at its lowest at cutting speed of 260 m/min and depth of cut of 0.1 mm respectively.

$v^*f$ : This plot indicates that how variables, cutting speed and feed are related to the surface roughness while the depth of cut is held at constant at middle level. The response is at its lowest when cutting speed of 260 m/min and feed of 0.04 mm/rev respectively.

From the 3D surface plots, the optimal parametric combination for lowest surface roughness is  $d1-f1-v3$  i.e.  $d = 0.1$  mm,  $f = 0.04$  mm/rev and  $v = 260$  m/min. Both have curvilinear profile in accordance to the quadratic model fitted.



**Fig. 7.** Surface plots of Ra

## 5. Conclusions

From the above investigations, it is concluded that the full factorial design gives a comparatively accurate prediction of surface roughness averages. From RSM model, regression is significant. Regression, linear, square and interaction terms are significant with P value less than 0.05. It is evident that, feed is the significant factor affecting surface roughness followed by cutting speed and depth of cut. It is observed that the maximum error between ANN model and experimental lies between -1.27 to 0.02 % which is significantly less than the RSM model. Hence, both the proposed RSM and ANN prediction model sufficiently predicts the surface roughness accurately. However, ANN prediction model is found to be better compared to RSM model (Sehgal & Meenu, 2013). From the 3D surface plots, the optimal parametric combination for lowest surface roughness is d1-f1-v3 i.e. d = 0.1 mm, f = 0.04 mm/rev and v = 260 m/min.

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