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TECHNICAL PAPER

Estimation of surface roughness using cutting parameters, force, sound, and vibration in turning of Inconel 718

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Abstract The present work is aimed at in-process estimation of surface roughness using cutting parameters along with cutting force, sound, and vibration in turning of Inconel 718 with cryogenically treated and untreated carbide inserts. Initially, prediction models are developed by regression analysis using only cutting parameters and then using only force, sound, and vibration. Later on, these models are modified to include all the parameters after performing correlation analysis for determining significant parameters. The modified models are developed using only significant parameters from the cutting parameters and measured responses. The prediction results of modified regression models are compared with experimental results and fine association of fit between measured and estimated surface roughness is confirmed. Based on coefficient of determination (R^2) values, the regression models are found to be better for estimating surface roughness. Finally, it is found that modified regression models are estimating surface roughness with more than 90% accuracy which can be said as acceptable for the two types of inserts used. Use of sound emitted while machining along with values of cutting parameters, force, and vibration to predict surface roughness has not been reported earlier particularly for Inconel 718. As cutting force, sound, and vibration can be measured during the turning process, this method can be useful for real-time control of the process to get the desired surface roughness for machining of difficult to cut material like Inconel 718.

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Keywords Surface roughness · Inconel 718 · Regression analysis · Cryogenic treatment

Abbreviations

CNC	Computer numerical control
CCD	Central composite design
MRA	Multiple regression analysis
RSM	Response surface methodology
FOE_C	First-order equation using cutting parameters
FOE_R	First-order equation using response parameters
FOE_M	Modified first-order equation
PCA	Pearson correlation analysis

List of symbols

v	Cutting speed (m/min)
f	Feed rate (mm/rev)
d	Depth of cut (mm)
F_c	Cutting force (N)
S	Sound pressure level (Pa)
V_v	Vibration velocity (m/s)
n	Number of experiments
R_{ai}	Average of measured surface roughness in μm
$\hat{R}_{ai}$	Estimated surface roughness
R^2	Coefficient of determination
AE	Absolute error (%)
MAE	Mean absolute error (%)
MSE	Mean square error (%)

1 Introduction

Surface roughness is important in any machining operation as it is directly related to the functional requirement of machined components. Component failure generally starts at the surface due to either a remote manufacturing discontinuity or gradual corrosion. Therefore, surface roughness investigation is essential for number of applications concerned with the control of friction, fatigue, and wear of parts [1]. Nowadays, machines work at higher speeds and loads which need higher dimensional and geometrical accuracies along with surface quality of the finished parts like bearings, seals, shafts, machine ways, gears, etc. The ability of a manufacturing process to produce desired surface finish depends on machine tool, cutting process, cutting parameters, work material, and cutting tool [2].

1.1 Methods used for surface roughness prediction

In the literature, various models showing relationship between surface roughness and cutting variables for the machining process are found. Whitehouse [3] proposed model with feed and the nose radius of tool. Fang and Safi-Jahanshahi [4] and Wang and Li [5] proposed models using cutting speed, feed, and depth of cut. These models are of limited use due to small range of cutting parameters covered and they do not include complex interactions among parameters.

These days, methods based on multiple regression modeling, response surface methodology (RSM), artificial neural network (ANN), and other advanced algorithms [6–17], etc., are used for prediction of surface roughness. Some such works using only cutting parameters are discussed below.

Krolczyk and Legutko [6] developed polynomial function of surface roughness to estimate the surface roughness in turning of duplex stainless steel and concluded that cost savings can be achieved. Pusavec et al. [7] developed performance-based prediction models using RSM for evaluating effect of cryogenic cooling and minimum quantity lubrication (MQL) in turning of Inconel 718. Davoodi and Tazehkandi [8] proposed an optimum range of cutting parameters for surface roughness and forces by establishing a model using RSM. Bhardwaj et al. [9] developed first-order and quadratic models for prediction of surface roughness and determined optimum cutting parameters using RSM in turning of EN 353. Ezilarasan et al. [10] determined the best machining conditions to reduce surface roughness by Taguchi method. They also used RSM to establish required correlation among the experimental and predicted values. Santhanakumar et al. [11] established the grey-based RSM approach in turning of 18% Ni maraging steel. They reported good surface quality and minimum flank wear with optimum machining parameters. Yahya et al. [12] performed end milling of AA6061 aluminum alloy to predict linear and non-linear models for surface roughness and cutting force using RSM and concluded that both models provided good results. Finally, optimization and verification of surface roughness were carried out. Ezugwu et al. [13] established the correlation among cutting and response parameters in turning of Inconel 718 using ANN. They optimized the process parameters for efficient and monetary production. Asilturk and Cunkas [14] developed a prediction model for the surface roughness using multiple regression and ANN with different training algorithms. Homani et al. [15] used joint optimization using neural network and genetic algorithm to arrive at the optimum cutting conditions for minimum surface roughness. Tamang and Chandrasekaran [16] integrated ANN model with particle swarn optimization (PSO) to optimize machining parameters of Inconel 825 for achieving good surface quality in minimum time. Sahu and Andhare [17] used RSM and teaching learning-based algorithm to determine the optimum cutting parameters for minimizing surface roughness. Later, they observed that using teaching–learning-based algorithm, minimum surface roughness could be achieved. From the literature, it is found that available techniques are reliable for accurate prediction of surface roughness.

The use of vibrations and cutting forces along with cutting parameters as input is made by a few researchers for prediction of surface roughness and such works are summarized in Table 1. Ozel and Karpat [18] used cutting parameters and cutting forces to predict surface roughness models. Risbood et al. [19] established models for the estimation of surface roughness using cutting parameters and vibration in radial direction. Upadhyay et al. [20] developed models for the estimation of surface roughness using different cutting parameters and tool vibrations. Kirby et al. [21] used multiple regression analysis (MRA) and analysis of variance (ANOVA) for showing a good association between feed rate and tool vibrations for estimation of surface roughness. It is found that only vibration is unable to predict surface roughness correctly. However, when vibrations are combined with cutting parameters, surface roughness is predicted accurately [18–21].

1.2 Surface roughness predictions for Inconel 718

Inconel is difficult to machine due the following reasons: Higher strength produces higher temperatures during machining. Because of low thermal conductivity (11.2 W/mK), more heat gets transferred to the tool causing further rise in tool temperature [22]. It has high hot hardness and high work hardening tendency [23, 24]. It has fine carbides in the microstructure which are abrasive in nature, which significantly reduce the tool life. The alloy also has tendency of the built-up edge formation which leads to reduced tool life and work finish [25–27]. Therefore, getting proper

Table 1 Application of cutting and response parameters for modeling of surface roughness in turning

References	Machining operation	Model inputs	Prediction accuracy
Ozel and Karpat [18]	Dry turning of AISI H 13 steel	Workpiece hardness, cutting speed, feed rate, cutting length, cutting forces	Average rms error of 9.3 and 5.4%
Risbood et al. [19]	Dry and wet turning of steel	Cutting speed, feed rate, depth of cut, and acceleration of radial vibration	Error less than 20% is reasonable
Upadhyay et al. [20]	Wet turning of Ti-6Al-4 V alloy	Cutting speed, feed rate, depth of cut, and vibration signals	Maximum error is 7.45% using MRA
Kirby et al. [21]	Dry turning of aluminum alloy ASTM B221	Cutting speed, feed rate, depth of cut, and vibration signals	Prediction errors of 9.96% for experimental and 10.77% in validation test

Table 2 Composition of workpiece material (Inconel 718)

Elements	Ni	Cr	Nb + Ta	Mo	Al	Co	Ti	Fe and other
% Weight	54.4	17.5	5.32	3.02	0.66	0.25	0.96	Balance

finish or control on surface roughness is very difficult for Inconel 718. It is observed that there is no extensive study for the prediction of surface roughness for Inconel 718 using the various models discussed so far. In the reported works, the prediction models are developed using the cutting parameters only. No information on the prediction of the surface roughness during the machining of Inconel 718 using cutting force, vibrations of work piece, and sound is available. However, these parameters are useful for process monitoring. Hence, in this study, it is proposed to employ the measured responses like cutting force (F_c), sound pressure level (S) at tool chip interface, and work piece vibration (V_v) for estimation of surface roughness for turning of Inconel 718 using multiple linear regression.

1.3 Error analysis in prediction model

In the models discussed above, for prediction of model accuracy, statistical techniques are used to find absolute error (AE), mean absolute error (MAE), and mean square error (MSE) in percentage. These are calculated with the following equations:

$$\text{Absolute error (\%)} = \left[\frac{\left|R_{ai} - \hat{R}_{ai}\right|}{R_{ai}} \times 100\right], \tag{1}$$

$$\text{Mean absolute error (\%)} = \left(\frac{1}{n}\right)\sum_{i=1}^{i=n}\left[\frac{\left|R_{ai} - \hat{R}_{ai}\right|}{R_{ai}} \times 100\right], \tag{2}$$

$$\text{Mean square error (\%)} = \left(\frac{1}{n}\right)\sum_{i=1}^{i=n}\left(R_{ai} - \hat{R}_{ai}\right)^2 \times 100. \tag{3}$$

In addition, the obtained values of coefficient of determination (R^2) are also used for comparing the capability of various developed models.

2 Experimentation

2.1 Workpiece and tool material

Hot rolled bars of Inconel 718 alloy of hardness 46 HRC and dimensions Ø 22 × 120 mm are selected for the machining. The chemical composition of material is shown in Table 2. Uncoated tungsten carbide inserts, TNMG 160408 (WIDIA make), with double chip breaker geometry are used as cutting tool. The specifications and structure of inserts are shown in Table 3. These tool inserts are used with and without cryogenic treatment to compare the performance in machining. However, for the work reported here, the objective is to predict the surface roughness based on force, sound, and vibration data. Hence, performance comparison of cryogenic treated (cryo treated) and untreated inserts is not reported in this paper. The selection and cryogenic treatment of tools, cutting conditions, and coolant type are based on the tool manufacturer's manual and references from the literature [7, 24, 28]. The details pertaining to the cutting

Table 3 Specification of tungsten carbide insert TNMG 160408

Shape	Inscribe circle diameter D (mm)	Thickness T (mm)	Cutting edge length $L10$ (mm)	Inside diameter $D1$ (mm)	Nose radius R_e (mm)
Triangular	9.53	4.76	16.5	3.81	0.8

conditions are as follows: cutting speed = 9.5 to 110.45 m/min, feed rate = 0.01 to 0.224 mm/rev, and depth of cut = 0.3 to 1.264 mm at constant cutting length of 20 mm. The fluid used in this process is Blasso-Cut 4000 oil, 8% volume mixed in water which is used through minimum quantity lubrication (MQL) system (make: DROPCO). The coolant pressure is kept at 4 bar with an approximate flow rate of 0.21 lph.

2.1.1 Details of cryogenic treatment of inserts

Cryogenic treatment of inserts is performed in the following manner: the inserts are cooled to temperature −196 °C in cryogenic chamber fitted with a computerized temperature controller. The cooling rate of 0.5 °C/min is maintained. The uniform temperature is achieved throughout the inserts in 8 h. The inserts are maintained at this temperature for 24 h. The inserts are brought to room temperature at the same rate in a time of 8 h. The entire duration of the cryogenic cycle is about 40 h. Subsequent to the cooling cycle, the inserts are tempered to release the stresses developed. Inserts are heated from room temperature to 196 °C in an hour. Further, they are held at that temperature for 2 h and cooled back to room temperature in an hour totalling the tempering duration to 4 h. The total duration of the cryogenic-double tempering cycle is 48 h.

2.2 Experiment setup

Experimental setup and turning of Inconel 718 are shown in Fig. 1. The turning is carried out on MTAB CNC lathe machine (Maxturn Plus +) rated output of 5.5 kW. The maximum centre distance is 360 mm. The swing over bed is about 235 mm and the maximum swing over carriage is 160 mm. The machine has a hydraulically operated three jaw chuck. The machine is equipped with eight stations turret and Siemen's Sinumerik 828D control. The cutting forces are measured using piezoelectric dynamometer (make: Kistler, type: 9257B) of range −5 to 10 kN. The charge developed by the dynamometer was amplified using a charge amplifier. The sound pressure level generated at tool–chip interface, while machining was measured in Pascal (Pa) using a free-field microphone probe with frequency range from 10 to 20 kHz (GRAS's 40PH CCP). The data of dynamometer and microphone are acquired with National Instrument's DAQ 9178 and stored in computer using LabVIEW 2012.

Many times, machining problems occur due to vibrations of tool and workpiece. Researchers have reported strong correlation among surface roughness and vibrations in machining process [29–31]. Hence, the measurement of vibrations is essential. Conventionally, the contact sensors are used to measure vibration of tool and work pieces in machining by mounting vibration transducers on the stationary part of machine. To avoid this limitation, recently, vibrations of rotating elements are measured precisely using noncontact type Laser Doppler Vibrometers. In the present work, laser type portable digital vibrometer (make: Polytech, PDV-100) is used for vibration measurement and data acquisition. The vibrometer is kept at a constant distance of 2 m from the machining setup. The laser beam of the vibrometer is adjusted, such that it focuses on the rotating workpiece shown in Fig. 1; during the machining and vibration velocity of workpiece (m/s) is measured. Similar method is reported by Prasad and Babu [31]. The vibrometer data are acquired with data acquisition card and stored in computer using VibSoft software. After completion of turning, the surface roughness of machined parts is measured with portable surface roughness tester (make: Mitutoyo, SURFTEST SJ-410). Average surface roughness (R_a) in microns is evaluated. The average of three measurements is noted equally at 120° on the circumference of each finished part. The measured values are then used for further analysis.

Fig. 1 Experimental setup with measuring instruments (*left*) and turning of Inconel 718 (*right*)

2.3 Experiment design

The experiments are designed using the central composite design (CCD) of RSM. Experimental design uses variation of three input parameters cutting speed (v), feed rate (f), and depth of cut (d) whose five levels are coded [32]. The coded and normal levels of the input variables are tabulated in Table 4. The outcome of design of experiment (DOE) shows 20 experiments along with six duplication of centre point according to the CCD using RSM in MINITAB 16 software. The design matrix and measured values of cutting force (F_c), machining sound (S), vibration (V_v), and surface roughness (R_a) using untreated and cryo treated inserts are listed in Table 5. In this table in columns 5–8, first value is for untreated inserts and second is for treated inserts. Using data of Table 5, three regression models are developed to predict surface roughness for turning with both the types of inserts used. The first model is developed with three cutting parameters (cutting speed, feed rate, and depth of cut), and the second model is developed using cutting force, vibration velocity, and sound pressure level recorded during experimentation. The third model is developed using only significant ones from the six parameters. These models and their performances are discussed in next part.

Table 4 Levels of cutting parameters for turning of Inconel 718

Cutting Parameters	Level 1	Level 2	Level 3	Level 4	Level 5
Coded	−1.682	−1	0	1	1.682
Cutting speed, v (m/min)	9.5	30	60	90	110.45
Feed rate, f (mm/rev)	0.01	0.05	0.115	0.18	0.224
Depth of cut, d (mm)	0.3	0.5	0.785	1.07	1.264

3 Results and discussion

3.1 Multiple regression analysis

The multiple linear regression analysis is a statistical method which identifies the correlation among dependent parameters and two or more independent parameters [33]. In this work, the surface roughness is estimated by the first-order regression equation developed using MINITAB 16 tool. All the regression equations developed are in uncoded units. Initially, the cutting speed, feed rate, and depth of cut are employed to develop the first-order regression equation (FOE_C) for estimation of F_c, S, V_v, and R_a for untreated and treated inserts. The cutting parameters are selected from Table 5 to obtain the models (4)–(11), respectively. Equations (4), (6), (8), (10) are developed for untreated inserts and (5), (7), (9), (11) are for cryo treated inserts giving F_c, S, V_v, and R_a, respectively.

Table 5 Design matrix and experimental responses

Run order	v (m/min)	f (mm/rev)	d (mm)	(Untreated/cryo treated)			
				F_c (N)	S (Pa)	$V_v \times 10^{-4}$ (m/sec)	R_a (µm)
1	90	0.18	1.07	200/190	0.270/0.260	13/12	1.78/1.79
2	9.5	0.115	0.785	617/602	0.794/0.780	37/36	2.30/2.40
3	30	0.18	0.5	463/456	0.531/0.633	33/23	2.20/2.20
4	60	0.01	0.785	231/225	0.210/0.209	16/15	0.99/1.00
5	60	0.115	0.785	455/445	0.472/0.462	26/25	0.93/0.99
6	60	0.115	1.264	404/390	0.501/0.487	23/24	1.49/1.80
7	110.45	0.115	0.785	163/160	0.190/0.189	13/13	0.62/0.60
8	30	0.18	1.07	590/580	0.791/0.781	36/35	2.20/2.30
9	60	0.115	0.785	459/551	0.660/0.652	27/25	0.93/0.98
10	60	0.115	0.785	461/555	0.691/0.686	29/26	0.99/0.95
11	90	0.18	0.5	279/270	0.130/0.123	19/17	1.25/1.21
12	90	0.05	1.07	190/185	0.198/0.192	12/11	0.52/0.75
13	60	0.224	0.785	444/440	0.509/0.491	32/30	2.40/2.50
14	60	0.115	0.785	464/461	0.521/0.511	28/27	0.99/1.10
15	30	0.05	1.07	447/442	0.422/0.412	29/28	1.60/1.60
16	30	0.05	0.5	436/432	0.421/0.419	27/26	1.90/1.36
17	60	0.115	0.785	471/476	0.567/0.559	28/26	0.92/1.10
18	60	0.115	0.305	300/295	0.321/0.312	26/24	1.30/1.35
19	60	0.115	0.785	451/445	0.563/0.558	30/29	0.93/1.17
20	90	0.05	0.5	150/147	0.161/0.158	12/11	0.72/0.76

Table 6 Estimated accuracy of developed FOE_C for R_a with percentage error

Inserts type	R^2 value (%)	MAE (%)	MSE (%)
Untreated	73.3	24.34	10.11
Cryo treated	78.8	19.13	7.91

Table 7 Estimated accuracy of developed FOE_R for R_a with percentage error

Inserts type	R^2 value (%)	MAE (%)	MSE (%)
Untreated	42.8	29.36	19.33
Cryo treated	48.8	27.11	16.53

$$F_c = 517.1 - 4.589v + 753f + 70.4d \quad \left(R^2 = 81.20\%\right)\left(R^2\text{adj} = 77.67\%\right), \tag{4}$$

$$F_c = 524.5 - 4.542v + 734f + 64.7d \quad \left(R^2 = 70.73\%\right)\left(R^2\text{adj} = 65.24\%\right), \tag{5}$$

$$S = 0.518 - 0.00591v + 1.154f + 0.190d \quad \left(R^2 = 67.60\%\right)\left(R^2\text{adj} = 61.53\%\right), \tag{6}$$

$$S = 0.546 - 0.00612v + 1.232f + 0.156d \quad \left(R^2 = 69.80\%\right)\left(R^2\text{adj} = 64.14\%\right), \tag{7}$$

$$V_v = 0.003589 - 0.000027v + 0.00547f - 0.000166d \quad \left(R^2 = 86.74\%\right)\left(R^2\text{adj} = 84.25\%\right), \tag{8}$$

$$V_v = 0.003122 - 0.000024v + 0.00412f + 0.000239d \quad \left(R^2 = 76.79\%\right)\left(R^2\text{adj} = 72.43\%\right), \tag{9}$$

$$\hat{R}_a = 1.56 - 0.0158v + 5.77f + 0.090d \quad \left(R^2 = 73.3\%\right)\left(R^2\text{adj} = 68.3\%\right), \tag{10}$$

$$\hat{R}_a = 1.21 - 0.0146v + 6.33f + 0.428d \quad \left(R^2 = 78.8\%\right)\left(R^2\text{adj} = 74.8\%\right). \tag{11}$$

For estimating the accuracy of models, the coefficient of determination (R^2), mean absolute error (MAE), and mean square error (MSE) are selected. For example, in case of R_a, the values of R^2 obtained from equations are 73.3 and 78.8% for the two types of inserts. Similarly, adjusted R^2 are 68.3 and 74.8%. Using data from Table 5 in (10) and (11), the estimated surface roughness values are evaluated. MAE and MSE in percentage for FOE_C are calculated and shown in Table 6 for untreated and cryo treated inserts.

In order to see if the measured responses, i.e., cutting force, sound pressure level, and vibration velocity, could be useful for predicting the surface roughness, the second model is developed using these responses only. The MRA is carried out using these responses. The first-order equations (FOE_R) are derived for estimation of surface roughness as function of cutting force, sound, and vibration using data of Table 5. The models are presented below as (12) and (13) for untreated and treated inserts, respectively. The values of coefficient of determination (R^2) obtained from above equations are 42.8 and 48.8% for the two types of inserts. Similarly, adjusted R^2 are 32.1 and 39.2%. Using experiment data from Table 5 in (12) and (13), the estimated surface roughness is evaluated and corresponding errors are presented in Table 7 for untreated and treated inserts. Both these errors are higher than acceptable:

$$\hat{R}_a = 0.067 - 1.36 \times 10^{-3}F_c - 0.82S + 873V_v \quad \left(R^2 = 42.8\%\right)\left(R^2\text{adj} = 32.1\%\right), \tag{12}$$

$$\hat{R}_a = 0.441 - 5.85 \times 10^{-3}F_c - 2.56S + 899V_v \quad \left(R^2 = 48.8\%\right)\left(R^2\text{adj} = 39.2\%\right). \tag{13}$$

As reported by Risbood et al. [19], Upadhyay et al. [20], and Kirby et al. [21], inclusion of cutting parameters along with cutting forces or vibration signals improves the prediction of surface roughness. Therefore, the first-order models (12) and (13) are modified by including three cutting parameters. Therefore, total six input parameters (cutting speed, feed rate, depth of cut, force, sound, and vibration) are used for developing a modified model. To identify the significant parameters amongst the six, Pearson correlation analysis (PCA) is carried out to establish correlation of input parameters with surface roughness. Range of correlation coefficient is between ±1 [20, 21]. A negative correlation gives inverse relationship and positive correlation signifies direct relationship between the variables. No association between the variables is indicated by zero value of correlation coefficient. From Table 8, it is observed that depth of cut is having correlation coefficient close to zero for untreated inserts; therefore, depth of cut does not have much effect on surface roughness and it can be removed in case of untreated inserts. In case of treated inserts, all the six parameters are having good correlation and hence are considered to establish modified regression model according to

Table 8 Pearson coefficient of parameters for surface roughness (untreated/cryo treated)

Parameter	v	f	D	F_c	S	V_v
Coefficient	−0.673/−0.636	0.528/0.593	0.036/0.177	0.542/0.470	0.451/0.525	0.621/0.600

PCA. Maximum value of Pearson coefficient is observed for cutting speed followed by vibration, cutting force, feed rate, and sound in that order for untreated inserts. Whereas, maximum value of Pearson coefficient is for cutting speed followed by vibration, feed rate, sound, cutting force, and depth of cut for cryo treated inserts. The values of Pearson coefficient are presented in Table 8. In each column, first value is for untreated inserts and next value is for treated inserts.

The effect of cutting parameters, force, sound, and vibration is observed from values obtained in Tables 5 and 8. The negative values of the cutting speed correlation coefficient for both treated and untreated inserts indicate that as the cutting speed increases, the surface roughness decreases. This is because as speed increases, there is more rapid cutting and rate of heat generation increases. This causes thermal softening of the work material resulting in reduced cutting force and better finish. The correlation coefficients for vibration velocity, sound pressure level, and cutting force indicate that, as these values increase, there is an increase in the surface roughness. This may be because rise in cutting force will result in larger amplitude of vibration and more sound adversely affecting the surface finish. Similarly, as feed increases, the cutting force increases, and because of this, the surface finish deteriorates. It is found that the depth of cut does not have significant effect on the surface finish.

The first-order regression model (12) for untreated inserts is modified by including cutting speed and feed rate only as coefficient for depth of cut is found to be close to zero. Equation (13) for treated inserts is modified including cutting speed, feed rate, and depth of cut. Modified first-order regression equations (FOE_M) for estimation of surface roughness for untreated and treated inserts are shown in (14) and (15), respectively. The coefficients of determination (R^2) values of FOE_M are obtained as 91.5 and 94.8% for untreated and treated inserts, respectively. Likewise, adjusted R^2 are 88.4 and 92.3%. Using (14) and (15), surface roughness values are predicted for the experimental data of Table 5. Predicted surface roughness values, percentage of MAE and MSE are shown in Table 9. Therefore, the accuracy of modified models (14) and (15) is enhanced with respect to models given in (10)–(13). The analysis of variance is used to evaluate significance of modified regression model for p and F ratio values, as shown in Table 10. In this table, also in every column, the first value is for untreated inserts and the second value is for treated inserts. The p value less than 0.05 and high F values of the modified models indicate that the models are extremely significant.

Table 9 Estimated accuracy of developed FOE_M for R_a with percentage error

Inserts type	R^2 value (%)	MAE (%)	MSE (%)
Untreated	91.5	9.82	2.88
Cryo treated	94.8	8.29	1.69

$$\hat{R}_\text{a} = 4.47 - 0.0381v + 9.95f - 2.03 \times 10^{-3}F_c - 0.023S - 481V_\text{v} \quad \left(R^2 = 91.5\%\right)\left(R^2\text{adj} = 88.4\%\right), \tag{14}$$

$$\hat{R}_\text{a} = 2.52 - 0.0259v + 8.04f + 0.582d - 3.87 \times 10^{-3}F_c + 0.365S + 166V_\text{v} \quad \left(R^2 = 94.8\%\right)\left(R^2\text{adj} = 92.3\%\right). \tag{15}$$

Residual and probability graphs for surface roughness for untreated and treated inserts are shown in Figs. 2 and 3. The developed modified regression models for estimated surface roughness using untreated and cryo treated inserts have been confirmed using residual examination. The four graphs for the both types of inserts are shown in Figs. 2a–d and 3a–d, respectively. It is seen from Figs. 2a and 3a that the residuals have close fit to a line in normal probability graphs, which signifies a good association between measured and estimated values. Figures 2b and 3b show least deviation among residuals and estimated values; residuals information are shown in histograms in Figs. 2c and 3c. Figures 2d and 3d show the residuals verses experiment data which spread up and down of zero line. It is concluded from the entire examination of residual and probability graphs that the models are capable for accurate estimation of surface roughness for both the types of inserts used. Therefore, for validating the models (14) and (15), fresh seven experiments are carried out with the similar range of cutting parameters as used in Table 4. The obtained values of responses and the cutting parameters are put in (14) and (15) to estimate the surface roughness values. The estimated roughness values are compared with the measured roughness values and the results are tabulated in Table 11. The percentage values of MAE for FOE_M are 8.37 and 9.62 for untreated and treated inserts.

Table 10 Analysis of variance (untreated/cryo treated)

Source of variations	Degrees of freedom	Sum of squares	Mean squares	*F* ratio	*p* value
Regression (14) and (15)	5/6	6.1867/6.1261	1.2373/1.0210	30.08/39.30	<0.0001/<0.0001
Residual error	14/13	0.5758/0.3378	0.0411/0.0260		
Total	19/19	6.7625/6.4639			

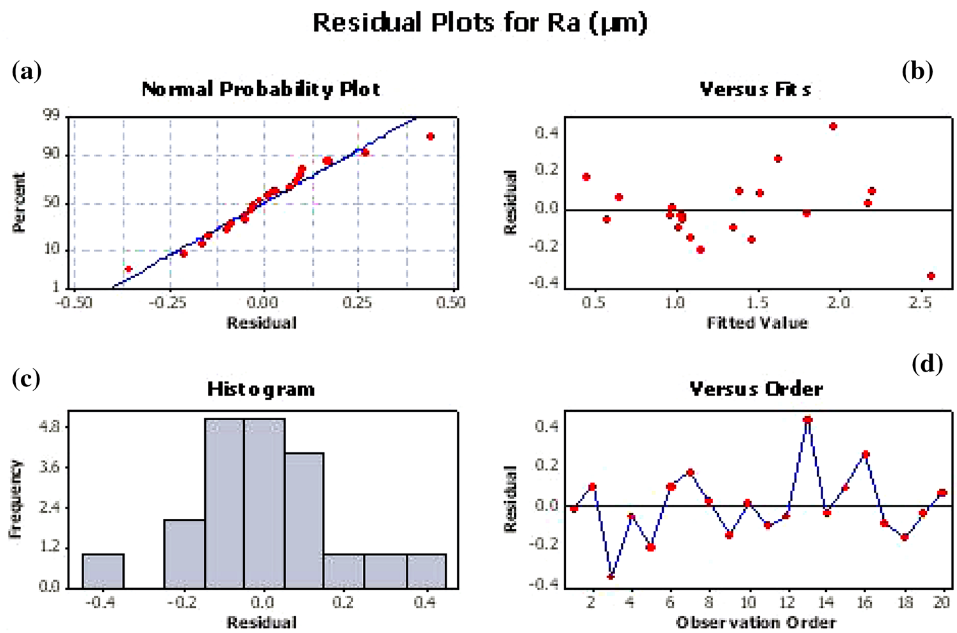

Fig. 2 Residual graphs for estimated surface roughness using untreated inserts: **a** normal probability plot, **b** residuals vs the fitted values, **c** residuals histogram, and **d** residuals vs the experimental data

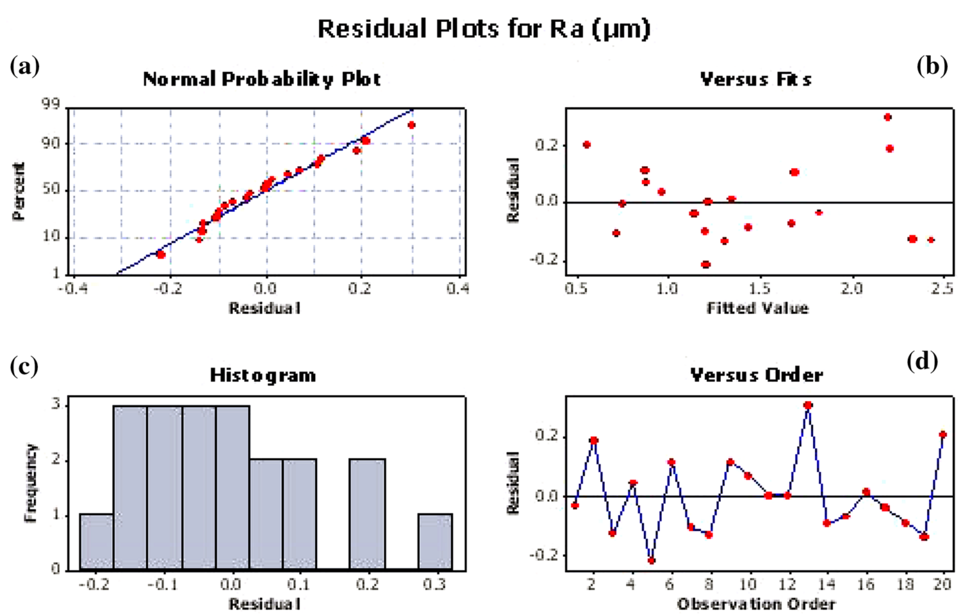

Fig. 3 Residual graphs for estimated surface roughness using cryo treated inserts: **a** normal probability plot, **b** residuals vs the fitted values, **c** residuals histogram, and **d** residuals vs the experimental data

Similarly, percentage values of MSE are 1.69 and 2.18, as shown in Table 11. Hence, it is evident that there is good agreement among estimated and experimental values of surface roughness using multiple regression analysis for both types of inserts.

4 Conclusion

The paper presented multiple regression-based models for estimation of surface roughness using cutting parameters along with cutting force, sound, and vibration in turning of

Table 11 Validation results for estimation of surface roughness

v (m/min)	*f* (mm/rev)	*d* (mm)	(Untreated/cryo treated)						
			F_c (N)	*S* (Pa)	$V_v \times 10^{-4}$ (m/s)	R_a (µm)	FOE_M		
							$\hat{R}_a$ (µm)	AE (%)	SE (%)
10	0.12	0.79	600/698	0.74/0.77	35/36	2.20/1.98	2.33/1.83	−6.08/7.43	1.79/2.17
60	0.12	0.79	450/410	0.455/0.52	26/29	1.30/1.32	1.15/1.43	11.26/−8.48	2.14/1.25
80	0.10	0.70	275/290	0.294/0.30	19/18	1.00/1.01	0.96/0.95	4.17/6.40	0.17/2.39
110	0.12	0.79	158/149	0.215/0.14	11/27	0.60/0.83	0.55/0.96	8.13/−16.07	0.24/1.78
60	0.22	0.79	445/436	0.51/0.25	32/20	2.10/1.77	1.96/1.96	6.60/−10.72	1.92/3.60
45	0.11	0.78	400/500	0.59/0.60	28/25	1.80/1.50	1.66/1.39	8.03/7.26	2.09/1.18
60	0.12	1.26	398/377	0.49/0.27	29/28	1.30/1.56	1.11/1.73	14.30/−10.95	3.45/2.92
Mean								8.37/9.62	1.69/2.18

Inconel 718. Three types of regression models are developed to predict surface roughness using untreated and cryo treated carbide inserts, and the prediction accuracy has been investigated on the basis of R^2, MAE, and MSE values.

The first model is developed using only the cutting parameters for estimation of force, sound, vibration, and surface roughness for untreated and treated inserts. The R^2 values for surface roughness are obtained as 73.3 and 78.8% for the two types of inserts. MAE and MSE are obtained as 24.34, 10.11, and 19.13%, and 7.91% for untreated and cryo treated inserts respectively. The second model is developed using the measured responses—cutting force, sound pressure level, and vibration velocity to estimate surface roughness for both the types of inserts. These models showed errors higher than acceptable. After performing Pearson correlation analysis, the third model is developed using only significant cutting parameters and measured responses for the two types of inserts. The modified regression models revealed different degrees of fitness for both types of inserts. R^2 values of the modified regression model are 91.5 and 94.8% for the untreated and treated inserts, respectively. It means that the models can explain 91.5 and 94.8% of total variations in surface roughness using cutting parameters, force, sound, and vibration. The percentage of MAE for main experiment and confirmation test data is 9.82, 8.37 and 8.29%, 9.62% for untreated and treated inserts, respectively. Similarly, the percentage of MSE for experimental and confirmation runs is 2.88, 1.69 and 1.69%, 2.18% for the two types of inserts.

The negative values of Pearson coefficient for the cutting speed in both types of inserts indicate that as the cutting speed increases, a better surface finish is obtained. This is because, with higher cutting speed, rate of heat generation increases, causing thermal softening of the work piece. This results in reduced cutting force and better surface finish. The Pearson coefficients for cutting force, sound pressure level, and vibration velocity are also indicators for surface roughness. With increment in values of indicators, the surface roughness increases. The rise in cutting force results in larger amplitude of vibration and sound, adversely affecting the surface finish. Likewise, increment in feed increases the cutting force which deteriorates the surface finish. It is found that the depth of cut does not have significant effect on the surface finish for both the types of inserts used. If performance of treated and untreated inserts is compared, there is no conclusive evidence that cryogenic treatment has resulted in better surface finish.

It can be concluded that using combination of cutting parameters and process responses, a strong relationship between estimated and measured surface roughness is observed while using treated or untreated inserts. It is found that the multiple regression analysis is a capable tool for estimating surface roughness with desirable accuracy for two types of inserts used for in-process monitoring. Application of measurement of sound emitted during machining along with values of cutting parameters, force, and vibration to predict surface roughness has not been reported earlier particularly for Inconel 718. As cutting force, sound, and vibration can be measured during the turning process, this method can be useful for real-time control of the process parameters to get the desired surface roughness value.

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