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Application of response surface methodology in describing the performance of coated carbide tools when turning AISI 1045 steel

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Abstract

The performance of a multilayer tungsten carbide tool was described using response surface methodology (RSM) when turning AISI 1045 steel. Cutting tests were performed with constant depth of cut and under dry cutting conditions. The factors investigated were cutting speed, feed and the side cutting edge angle (SCEA) of the cutting edge. The main cutting force, i.e. the tangential force and surface roughness were the response variables investigated. The experimental plan was based on the face centred, central composite design (CCD). The experimental results indicate that the proposed mathematical models suggested could adequately describe the performance indicators within the limits of the factors that are being investigated. The feed is the most significant factor that influences the surface roughness and the tangential force. However, there are other factors that provide secondary contributions to the performance indicators. In the case of surface roughness, the $SCEA^2$ and the interaction of feed and SCEA provides these contributions whilst for tangential force, the $SCEA^2$, the interaction of feed and SCEA; and the cutting speed provides them.
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Keywords: Coated carbide; RSM; SCEA; Surface roughness; Tangential force; Turning

1. Introduction

Machinability of a material provides an indication of its adaptability to be manufactured by a machining process. In general, machinability can be defined as an optimal combination of factors such as low cutting force, high material removal rate, good surface integrity, accurate and consistent workpiece geometrical characteristics, low tool wear rate and good curl or chip breakdown of chips.

In machinability studies investigations, statistical design of experiments is used quite extensively. Statistical design of experiments refers to the process of planning the experiment so that the appropriate data can be analysed by statistical methods, resulting in valid and objective conclusions [1]. Design and methods such as factorial design, response surface methodology (RSM) and Taguchi methods are now widely use in place of one-factor-at-a-time experimental approach which is time consuming and exorbitant in cost.

Thomas et al. [2] used a full factorial design involving six factors to investigate the effects of cutting and tool parameters on the resulting surface roughness and on built-up edge formation in the dry turning of carbon steel. The Taguchi method was used by Yang and Tarng [3] to find the optimal cutting parameters for turning operations. Choudhury and El-Baradie [4] had used RSM and 2^3 factorial design for predicting surface roughness when turning high-strength steel. Thiele and Melkote [5] had used a three-factor complete factorial design to determine the effects of workpiece hardness and cutting tool edge geometry on surface roughness and machining forces. The Taguchi method with multiple performance characteristics was used by Nian et al. [6] in the optimisation of turning operations. A polynomial network was used by Lee et al. [7] to develop a machining database for turning operations. On the other hand, Lin et al. [8] used an abductive network to construct a prediction model for surface roughness and cutting force. In combination, cutting speed, feed rate and depth of cut were the primary factors investigated whilst tool nose radius, tool length, edge preparation of tool, workpiece length and workpiece hardness were the secondary factors considered by the aforementioned investigators.

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Nomenclature

A	first factor or input variable investigated—cutting speed (m/min)
Adeq. precision	adequate precision
Adj. R^2	adjusted R^2
B	second factor or input variable investigated—feed (mm/rev)
C	third factor or input variable investigated—SCEA (°)
Cor. total	totals of all information corrected for the mean
CV	coefficient of variation
d.f.	degrees of freedom
F_c	main cutting force, i.e. tangential force (N)
Pred. R^2	predicted R^2
Prob. > F	proportion of time or probability you would expect to get the stated F value
PRESS	predicted residual error sum of squares
R_a	surface roughness of the turned surface (μ)
R^2	coefficient of determination
SCEA	side cutting edge angle (°)
S.D.	square root of the residual mean square

One of the most important parameters in tool geometry is the side cutting edge angle (SCEA). It serves two purposes in that it protects the point from taking the initial shock of the cut and it serves to thin out the chip by distributing the cut over a greater surface [9]. In this study, the SCEA has been taken into consideration along with cutting speed and feed as the factors to be investigated in describing the performance of coated carbide tools when turning AISI 1045 steel. This is due to the fact that SCEA has not been investigated previously during modelling inspite of its importance. Emphasis is however being placed towards studying the effects of negative SCEA in view of the fact that considerable research has been done to investigate the effect of positive SCEA, whereas published material on the performance of negative SCEA is somewhat limited [10,11]. Noordin et al. [12] found that the level of deformation of the chips is very low when the tool with −5° SCEA is being used at low feed rate. RSM will be used to identify the factors which influences the surface roughness and the main cutting force. Additionally these relationships will be quantified using mathematical modelling.

2. Response surface methodology

RSM is a collection of mathematical and statistical techniques that are useful for the modelling and analysis of problems in which a response of interest is influenced by several variables and the objective is to optimise this response [1]. RSM also quantifies relationships among one or more measured responses and the vital input factors [13].

The version 6 of the Design Expert software was used to develop the experimental plan for RSM. The same software was also used to analyse the data collected by following the steps as follows [13]:

1. Choose a transformation if desired. Otherwise, leave the option at "None".
2. Select the appropriate model to be used. The Fit Summary button displays the sequential F-tests, lack-of-fit tests and other adequacy measures that could be used to assist in selecting the appropriate model.
3. Perform the analysis of variance (ANOVA), post-ANOVA analysis of individual model coefficients and case statistics for analysis of residuals and outlier detection.
4. Inspect various diagnostic plots to statistically validate the model.
5. If the model looks good, generate model graphs, i.e. the contour and 3D graphs, for interpretation. The analysis and inspection performed in steps (3) and (4) above will show whether the model is good or otherwise. Very briefly, a good model must be significant and the lack-of-fit must be insignificant. The various coefficient of determination, R^2 values should be close to 1. The diagnostic plots should also exhibit trends associated with a good model and these will be elaborated subsequently.

After analysing each response, multiple response optimisation was performed, either by inspection of the interpretation plots, or with the graphical and numerical tools provided for this purpose.

It was mentioned previously that RSM designs also help in quantifying the relationships between one or more measured responses and the vital input factors. In order to determine if there exist a relationship between the factors and the response variables investigated, the data collected must be analysed in a statistically sound manner using regression. A regression is performed in order to describe the data collected whereby an observed, empirical variable (response) is approximated based on a functional relationship between the estimated variable, y_{est} and one or more regressor or input variable $x_1, x_2, \ldots, x_i$. In the case where there exist a non-linear relationship between a particular response and three input variables, a quadratic equation, $y_{est} = b_0 + b_1x_1 + b_2x_2 + b_3x_3 + b_4x_1x_2 + b_5x_1x_3 + b_6x_2x_3 + b_7x_1^2 + b_8x_2^2 + b_9x_3^2 + \text{error}$, may be used to describe the functional relationship between the estimated variable, y_{est} and the input variables x_1, x_2 and x_3. The least square technique is being used to fit a model equation containing the said regressors or input variables by minimising the residual error measured by the sum of square deviations between the actual and the estimated responses. This involves the calculation of estimates for the regression coefficients, i.e. the coefficients of the model variables including the intercept or constant term. The calculated coefficients or the model equation need to however be tested for statistical significance. In this respect, the following test are performed [14].

2.1. Test for significance of the regression model

This test is performed as an ANOVA procedure by calculating the *F*-ratio, which is the ratio between the regression mean square and the mean square error. The *F*-ratio, also called the variance ratio, is the ratio of variance due to the effect of a factor (in this case the model) and variance due to the error term. This ratio is used to measure the significance of the model under investigation with respect to the variance of all the terms included in the error term at the desired significance level, α. A significant model is desired.

2.2. Test for significance on individual model coefficients

This test forms the basis for model optimisation by adding or deleting coefficients through backward elimination, forward addition or stepwise elimination/addition/exchange. It involves the determination of the *P*-value or probability value, usually relating the risk of falsely rejecting a given hypothesis. For example, a "Prob. $>F$" value on an *F*-test tells the proportion of time you would expect to get the stated *F*-value if no factor effects are significant. The "Prob. $>F$" value determined can be compared with the desired probability or α-level. In general, the lowest order polynomial would be chosen to adequately describe the system.

2.3. Test for lack-of-fit

As replicate measurements are available, a test indicating the significance of the replicate error in comparison to the model dependent error can be performed. This test splits the residual or error sum of squares into two portions, one which is due to pure error which is based on the replicate measurements and the other due to lack-of-fit based on the model performance. The test statistic for lack-of-fit is the ratio between the lack-of-fit mean square and the pure error mean square. As previously, this *F*-test statistic can be used to determine as to whether the lack-of-fit error is significant or otherwise at the desired significance level, α. Insignificant lack-of-fit is desired as significant lack-of-fit indicates that there might be contributions in the regressor–response relationship that are not accounted for by the model.

Additionally, checks need to be made in order to determine whether the model actually describes the experimental data [14]. The checks performed here include determining the various coefficient of determination, R^2. These R^2 coefficients have values between 0 and 1. In addition to the above, the adequacy of the model is also investigated by the examination of residuals [1]. The residuals, which are the difference between the respective, observe responses and the predicted responses are examined using the normal probability plots of the residuals and the plots of the residuals versus the predicted response. If the model is adequate, the points on the normal probability plots of the residuals should form a straight line. On the other hand the plots of the residuals versus the predicted response should be structureless, that is, they should contain no obvious patterns.

3. Experimental details

3.1. Cutting inserts

Coated carbide tools have been known to perform better than uncoated carbide tools when turning steel [1–3,15–17]. For this reason, commercially available CVD coated carbide insert was used in this investigation. The inserts were manufactured by Kennametal Inc., with the ISO designation of CNMG 120408-FN (80° diamond-shaped insert) and TNMG 120408-FN (60° triangular-shaped insert). The FN designation indicates that it has a chipbreaker for finishing with a negative, stable cutting edge style. The 80° diamond-shaped insert is one of the popular inserts used with negative SCEA. With this configuration it can be used for seven operations as compared to the square or triangular shape. The use of a −5° SCEA enables both facing and turning to be done with the same tool which is a big advantage in a CNC machine tool [10]. In both instances the grade of the coated carbide used is designated by KC 9010 and the nose radius is 0.8 mm. KC 9010 is a thick alumina-coated grade with a moderately hard, deformation resistant substrate and it is CVD coated with TiCN underlayer, followed by Al_2O_3 intermediate layer and TiN outerlayer. The provision of a functional TiN outerlayer reduces the tendency to built-up edges. Furthermore, the generation of heat is less owing to the reduction of friction. This resulted in less thermal cracks and increases tool life. In addition, any wear pattern can be easily recognised with the yellow TiN layer [18]. As the investigation involves the performance evaluation of coated carbide tool having side cutting edge angles (SCEA) of −5°, −3° and 0°, the inserts were rigidly mounted on three different right hand style tool holders designated by ISO as MCLNR 2525 M12, MTJNR 2525 M16 and MTGNR 2525 M16 thus giving side cutting angle of −5°, −3° and 0°, respectively. In all instances, the back rake angle and the side rake angle is −5°.

3.2. Workpiece materials

The cutting performance tests were performed on AISI 1045 steel bars. Its composition is 0.45%C, 0.72%Mn, 0.20%Si, 0.015%P, 0.018%S, 0.10%Cu, 0.09%Ni and 0.07%Cr. The hardness of the bar is 187 HB. The workpiece material used has a dimension of 300 mm in length and 100 mm in diameter. This material is suitable for a wide variety of automotive-type applications [19]. Axle and spline shaft are two examples of automotive components produced using this material where the turning is the prominent machining process used.

Table 1
Factors and levels for response surface study

Factor	Low level (−1)	High level (+1)
A–cutting speed (m/min)	240	375
B–feed (mm/rev)	0.18	0.28
C–SCEA (°)	−5	0

3.3. Cutting conditions and experimental plan

In this particular investigation three factors are being studied and their low and high levels are given in Table 1. Cutting tests were carried out on a 9.2 kW Harrison M500 lathe machine under dry cutting conditions. High feed rates were also considered for high productivity reasons. Machining was performed dry as dry machining has been considered as the machining of the future due to concern regarding the safety of the environment [20]. A low depth of cut (d) of 1 mm was used for near net shape manufacturing and was kept constant throughout the tests. The conditions were selected after considering the recommendations given in the tool manufacturer's catalogue [21,22].

The turning process was studied with a standard RSM design called a central composite design (CCD) whereby the factorial portion is a full factorial design with all combinations of the factors at two levels, the star points are at the face of the cube portion on the design which corresponds to an α-value of 1 and this is commonly referred to as a face-centred, CCD and the centre points, as implied by the name, are points with all levels set to coded level 0—the midpoint of each factor range and this is repeated twice. The response variables investigated are the surface roughness of the turned surface, R_a and the main cutting force, i.e. the tangential force, F_c. Based on the foregoing input and upon editing the completed design layout produced by the software so as to reflect the actual midpoint values to be used, i.e. 300 m/min for cutting speed and −3° for SCEA, the revised design layout is as shown in Table 2. It has been shown that small discrepancies in the required factor levels will result in very little difference in the model subsequently developed and the practical interpretation of the results of the experiments would not be seriously affected by the inability of the experimenter to achieve the desired factor levels exactly [1].

3.4. Experimental techniques

As shown in Section 3.3, the cutting performance tests involved 16 trials and the response variables measured were the main cutting force, F_c and the surface roughness. The cutting force was measured using a three-component dynamometer (Kistler, Type 9265B), a multichannel charge amplifier (Kistler, Type 5019A) and a data acquisition system. The surface roughness of the turned surface was measured using a portable surface roughness tester (Rank Taylor Hobson, Surtronic 3+). For each experimental trial, a new cutting edge was used. Due to the limited number of inserts available, each experimental trial was repeated twice and each surface turned was measured at three different locations. As far as possible the trials were performed in a random fashion.

Table 2
Completed design layout

Std. run no.	Run	Block	Factor		
			A—cutting speed (m/min)	*B*—feed (mm/rev)	*C*—SCEA (°)
1	8	1	240	0.18	−5
2	9	1	375	0.18	−5
3	12	1	240	0.28	−5
4	15	1	375	0.28	−5
5	13	1	240	0.18	0
6	3	1	375	0.18	0
7	11	1	240	0.28	0
8	2	1	375	0.28	0
9	14	1	240	0.23	−3
10	16	1	375	0.23	−3
11	6	1	300	0.18	−3
12	7	1	300	0.28	−3
13	1	1	300	0.23	−5
14	4	1	300	0.23	0
15	10	1	300	0.23	−3
16	5	1	300	0.23	−3

4. Results and discussion

The results from the machining trials performed as per the experimental plan are shown in Table 3. These results were input into the Design Expert software for further analysis following the steps outlined in Section 2. Without performing any transformation on the response, examination of the Fit Summary output revealed that the quadratic model is statistically significant for both responses and therefore it will be used for further analysis.

Table 3
Experimental results

Std. run no.	Surface roughness, R_a (μ)	Tangential force, F_c (N)
1	1.68	395.98
2	1.40	372.24
3	3.18	550.14
4	2.95	525.85
5	1.20	372.83
6	1.42	366.48
7	3.80	559.22
8	3.25	553.50
9	2.14	443.10
10	2.08	432.27
11	1.14	351.14
12	2.99	540.77
13	2.17	440.92
14	2.32	465.40
15	1.76	436.10
16	1.74	428.88

Table 4
ANOVA table (partial sum of squares) for response surface quadratic model (response: surface roughness, R_a)

Source	Sum of squares	d.f.	Mean square	F	Prob. > F
Model	9.71	9	1.08	35.59	0.0002 significant
A	0.080	1	0.080	2.62	0.1564
B	8.77	1	8.77	289.44	<0.0001
C	0.038	1	0.038	1.24	0.3075
A^2	0.050	1	0.050	1.66	0.2449
B^2	0.018	1	0.018	0.60	0.4678
C^2	0.16	1	0.16	5.43	0.0586
AB	0.065	1	0.065	2.16	0.1922
AC	0.0028	1	0.0028	0.091	0.7729
BC	0.24	1	0.24	7.86	0.0310
Residual	0.18	6	0.030		
Lack-of-fit	0.18	5	0.036	181.67	0.0563 not significant
Pure error	0.0002	1	0.0002		
Cor. total	9.89	15			
S.D.	0.17	R^2	0.9816		
Mean	2.20	Adj. R^2	0.9540		
CV	7.91	Pred. R^2	0.7502		
PRESS	2.47	Adeq. precision	19.16		

4.1. ANOVA analysis

It was previously mentioned that test for significance of the regression model, test for significance on individual model coefficients and test for lack-of-fit need to be performed. An ANOVA table is commonly used to summarise the tests performed. Table 4 shows the ANOVA table for response surface quadratic model for surface roughness.

The value of "Prob. > F" in Table 4 for model is less than 0.05 which indicates that the model is significant, which is desirable as it indicates that the terms in the model have a significant effect on the response. In the same manner, the main effect of feed (B) and the two-level interaction of feed and SCEA (BC) are significant model terms. Other model terms can be said to be not significant. These insignificant model terms (not counting those required to support hierarchy) can be removed and may result in an improved model. The lack-of-fit can also be said to be insignificant. This is desirable as we want a model that fits.

By selecting the backward elimination procedure to automatically reduce the terms that are not significant, the resulting ANOVA table for the reduced quadratic model for surface roughness is shown in Table 5. Results from Table 5 indicate that the model is still significant. However, the main effect of feed (B), the second-order effect of SCEA (C^2) and the two-level interaction of feed and SCEA (BC) are the significant model terms. The main effect of SCEA (C) was added to support hierarchy. The main effect of feed (B) is the most significant factor associated with surface roughness.

This is expected because it is well known that for a given tool nose radius, the classical surface roughness is primarily a function of the feed [23]. Additionally, the results show that the SCEA^2 and the interaction between the feed and SCEA terms provide secondary contribution to the surface roughness. The lack-of-fit can still be said to be insignificant. The R^2 value is high, close to 1, which is desirable. The predicted R^2 is in reasonable agreement with the adjusted R^2. The adjusted R^2 value is particularly useful when comparing models with different number of terms. This comparison is however done in the background when model reduction is taking place. Adequate precision compares the range of the predicted values at the design points to the average prediction error. Ratios greater than 4 indicate adequate model discrimination. In this particular case the value is well above 4.

The same procedure is applied on response F_c and the resulting ANOVA table for the reduced quadratic model is shown in Table 6. For F_c, the main effects of cutting speed (A) and feed (B), the second-order effect of SCEA (C^2) and the two-level interaction of feed and SCEA (BC) are the significant model terms. As before, the main effect of SCEA (C) was added to support hierarchy. Interestingly, significantly better statistics were obtained. The feed factor is the most significant factor associated with the tangential force. This can be explained by the fact that the undeformed chip thickness increases with increasing feed and the tangential force is proportional to the undeformed chip thickness. Additionally, the results show that the SCEA^2, the interaction between the feed and SCEA; and the cutting speed provide secondary contributions to the tangential force.

The following equations are the final empirical models in terms of coded factors for:

- Surface roughness, R_a:

$$R_a = 1.97 + 0.94B + 0.06C + 0.36C^2 + 0.17BC \qquad (1)$$

- Tangential force, F_c:

$$F_c = 437.96 - 6.93A + 87.39B + 3.23C + 22.15C^2 + 7.76BC \qquad (2)$$

Table 5
Resulting ANOVA table (partial sum of squares) for reduced quadratic model (response: surface roughness, R_a)

Source	Sum of squares	d.f.	Mean square	F	Prob. > F
Model	9.47	4	2.37	62.07	<0.0001 significant
B	8.82	1	8.82	231.11	<0.0001
C	0.037	1	0.037	0.98	0.3445
C^2	0.45	1	0.45	11.85	0.0055
BC	0.24	1	0.24	6.22	0.0298
Residual	0.42	11	0.038		
Lack-of-fit	0.42	10	0.042	209.70	0.0537 not significant
Pure error	0.0002	1	0.0002		
Cor. total	9.89	15			
S.D.	0.20	R^2	0.9576		
Mean	2.20	Adj. R^2	0.9421		
CV	8.87	Pred. R^2	0.8976		
PRESS	1.01	Adeq. precision	22.35		

Table 6
Resulting ANOVA table (partial sum of squares) for reduced quadratic model (response: tangential force, F_c)

Source	Sum of squares	d.f.	Mean square	F	Prob. > F
Model	7.86E+04	5	1.57E+04	168.78	<0.0001 significant
A	482.40	1	482.40	5.18	0.0462
B	7.62E+04	1	7.62E+04	817.91	<0.0001
C	104.33	1	104.33	1.12	0.3149
C^2	1668.17	1	1668.17	17.90	0.0017
BC	485.13	1	485.13	5.21	0.0457
Residual	931.90	10	93.19		
Lack-of-fit	905.84	9	100.65	3.86	0.3769 not significant
Pure error	26.06	1	26.06		
Cor. total	7.96E+04	15			
S.D.	9.65	R^2	0.9883		
Mean	452.18	Adj. R^2	0.9824		
CV	2.13	Pred. R^2	0.9714		
PRESS	2279.00	Adeq. precision	35.91		

While, the following equations are the final empirical models in terms of actual factors for:

- Surface roughness, R_a:

$$R_a = -2.714 + 22.228\,\text{feed} + 2.88 \times 10^{-4}\,\text{SCEA} + 0.0583\,\text{SCEA}^2 + 1.372\,\text{feed} \times \text{SCEA} \quad (3)$$

- Tangential force, F_c:

$$F_c = 57.237 - 0.103\,\text{cutting speed} + 1902.95\,\text{feed} + 4.737\,\text{SCEA} + 3.543\,\text{SCEA}^2 + 62.05\,\text{feed} \times \text{SCEA} \quad (4)$$

The normal probability plots of the residuals and the plots of the residuals versus the predicted response for surface roughness and tangential force are shown in Figs. 1–4, respectively. A check on the plots in Figs. 1 and 3 revealed that the residuals generally fall on a straight line implying that the errors are distributed normally. Also Figs. 2 and 4 revealed that they have no obvious pattern and unusual structure. This implies that the models proposed are adequate and there is no reason to suspect any violation of the independence or constant variance assumption.

The 3D surface graphs for surface roughness and tangential force are shown in Figs. 5 and 6. Both have curvilinear profile in accordance to the quadratic model fitted. The contour for the response surface for surface roughness is shown in Fig. 7. It is clear from Fig. 7 that at any particular feed, the best surface finish is obtainable when the SCEA is somewhere at middle of the SCEA range experimented. This is consistent with the fact that the SCEA^2 term is significant. Also at lower feeds, better surface finish is obtainable at 0° SCEA compared to −5° SCEA. However at feeds above approximately 0.22 mm/rev, the reverse happens, i.e. better surface roughness is obtainable at −5° SCEA compared to 0° SCEA. This is as a result of the contribution of the interaction effect between the feed and SCEA which was one of the significant model term (see Fig. 8). It is also clear from Fig. 7 that the surface roughness increases with increasing feed. The same observation can also be made for tangential force. However, as the cutting speed was also a significant factor, the tangential force is also dependent on it. Response surface contours at any particular cutting speed can be obtained.

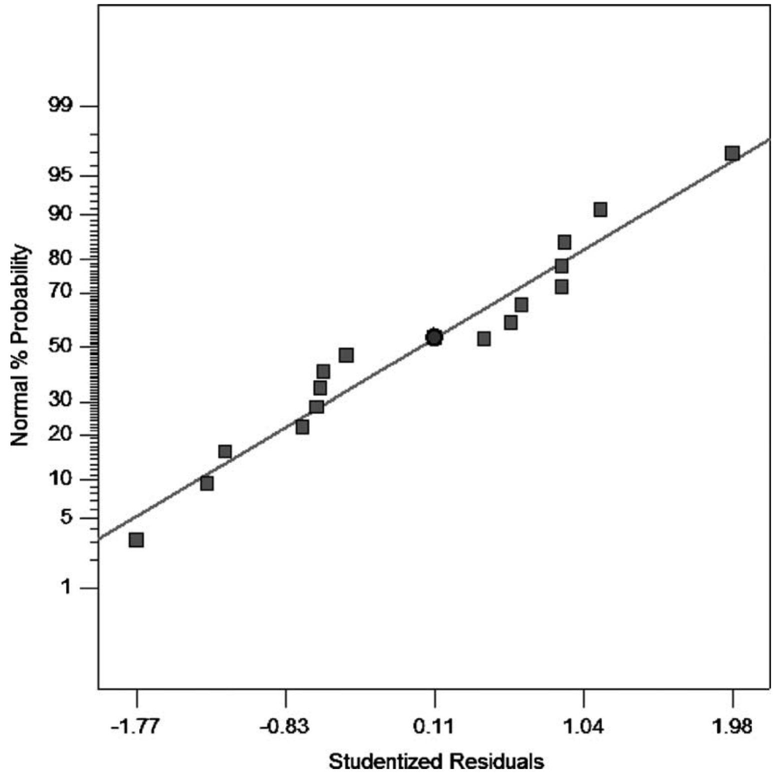

Fig. 1. Normal probability plot of residuals for R_a data.

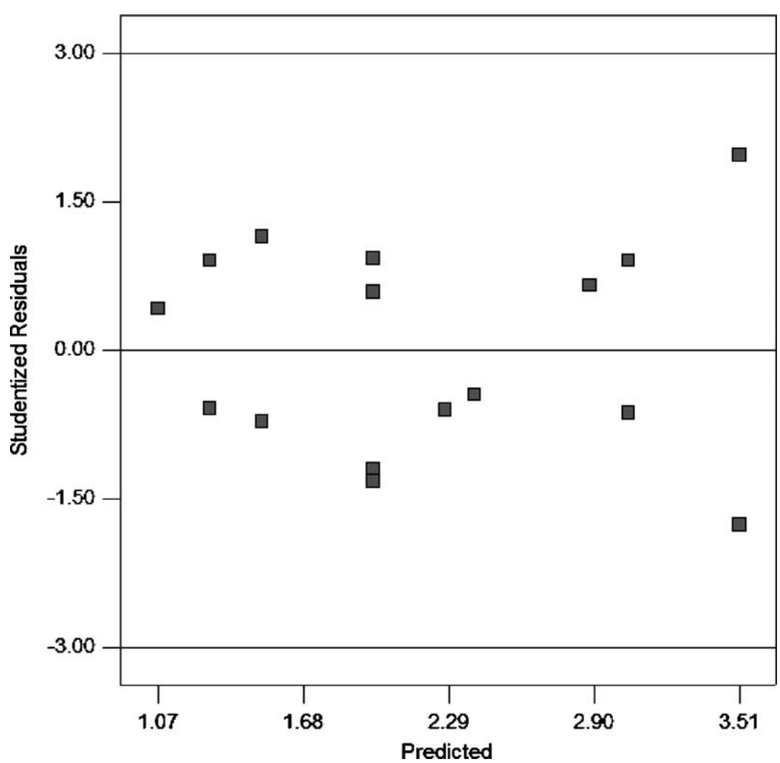

Fig. 2. Plot of residuals vs. predicted response for R_a data.

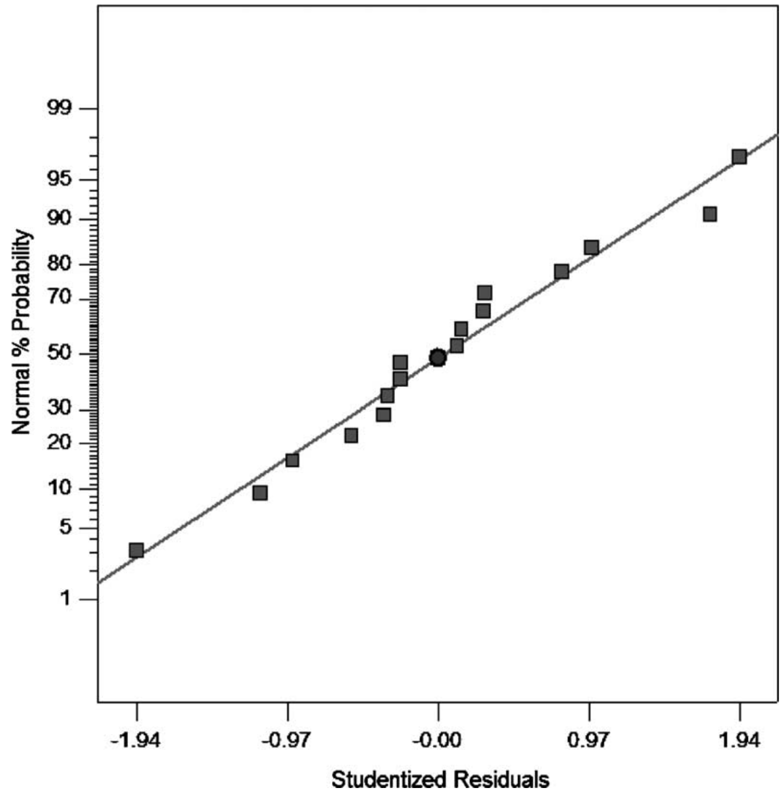

Fig. 3. Normal probability plot of residuals for F_c data.

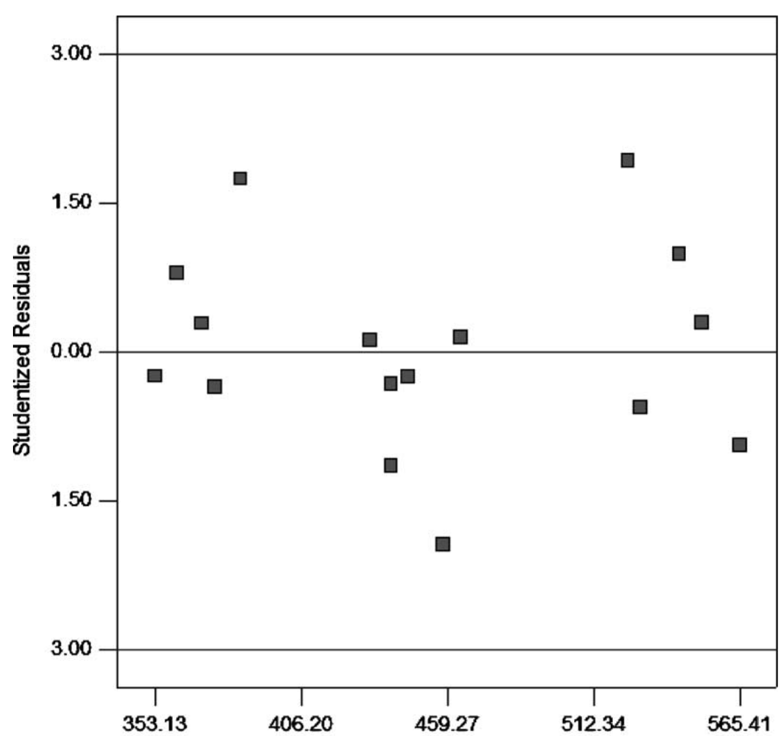

Fig. 4. Plot of residuals vs. predicted response for F_c data.

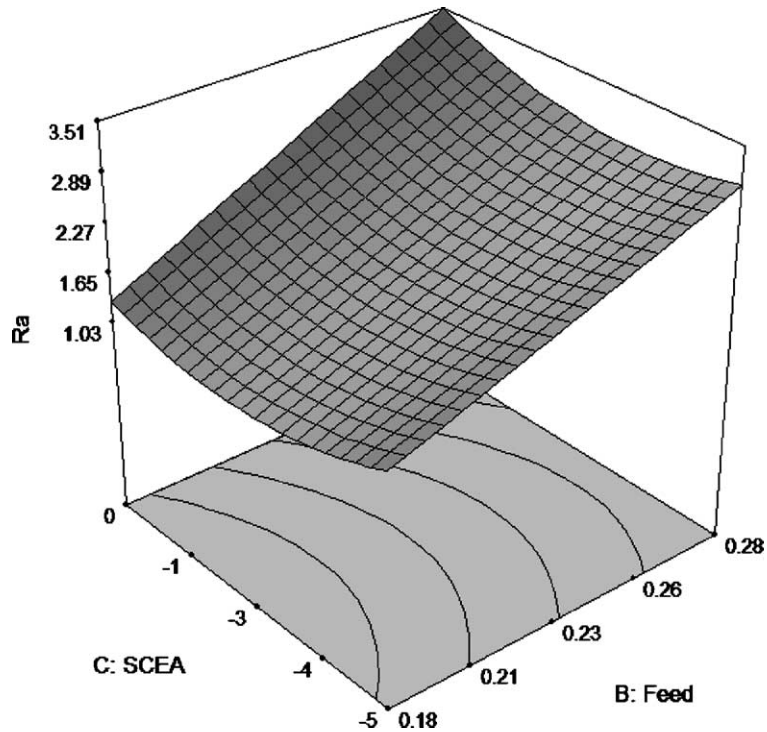

Fig. 5. 3D surface graph for surface roughness.

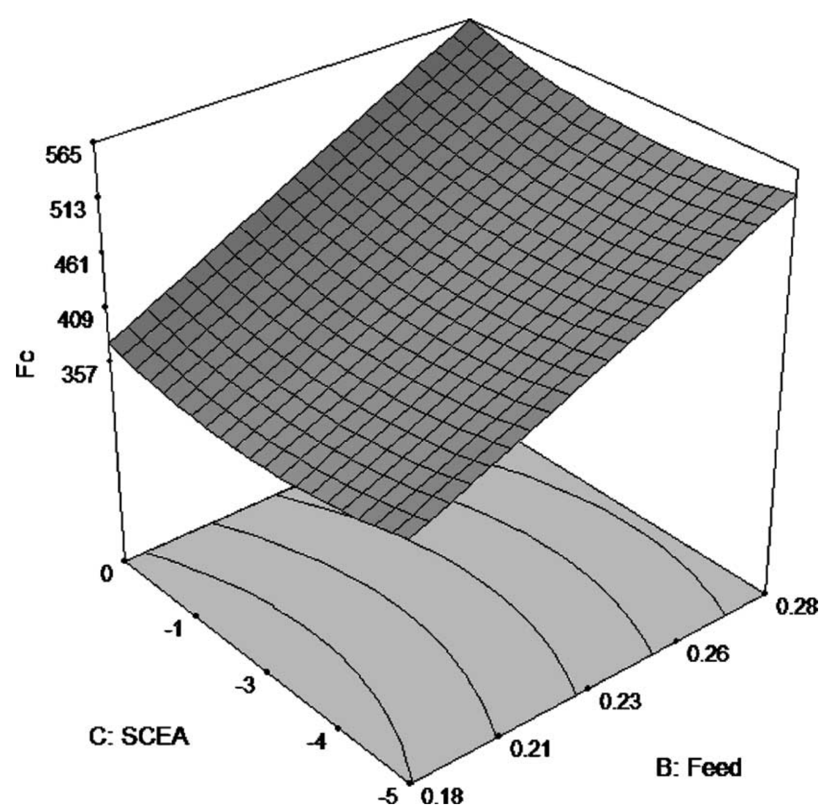

Fig. 6. 3D surface graph for tangential force.

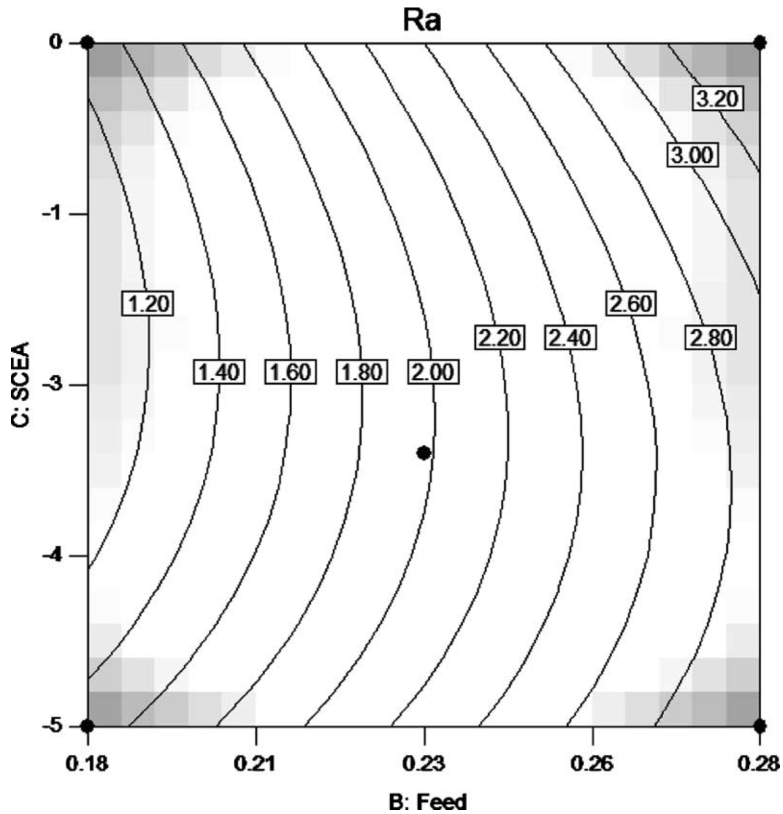

Fig. 7. R_a contours in feed–SCEA plane at cutting speed of 300 m/min.

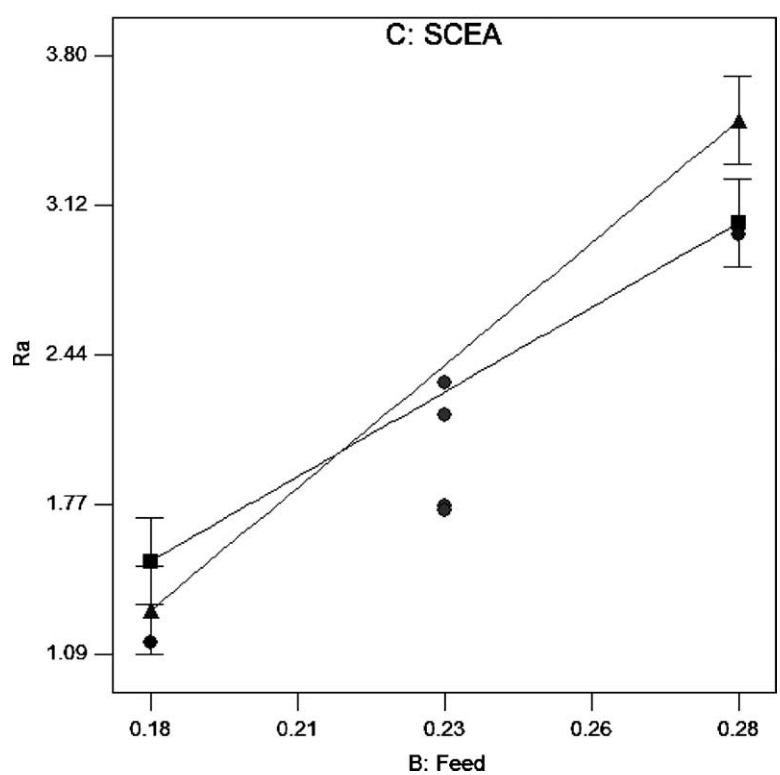

Fig. 8. Graph showing the interaction between feed and SCEA (▲ for 0°, ■ for −5°) for R_a (● are design points).

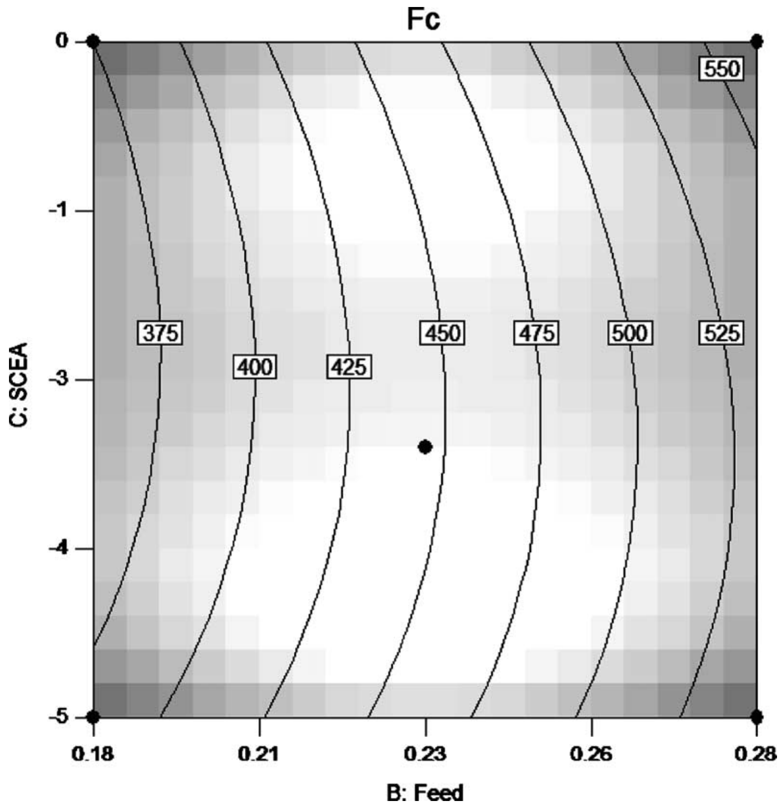

Fig. 9. Tangential force contours in feed–SCEA plane at cutting speed of 240 m/min.

Figs. 9 and 10 are the said contours at cutting speeds of 240 and 375 m/min. The two contours are almost similar except that at 375 m/min the tangential forces are lower than those at 240 m/min. Both the contours are also similar to those for surface roughness and therefore the comments given previously for surface roughness hold true for tangential force.

Overlay plots can also be produced by superimposing the contours for the various response surfaces. By defining the limits of the surface roughness and forces desired, the shaded portion of the overlay plot, as shown in Fig. 11, defines the permissible values of the dependent variables.

4.2. Confirmation test

In order to verify the adequacy of the model developed, six confirmation run experiments were performed (Table 7). The test condition for first three confirmation run experiments were among the cutting conditions that were performed previously whilst the remaining three confirmation run experiments were conditions that have not been used previously but are within the range of the levels defined previously. Using the point prediction capability of the software, the surface roughness and the tangential force of the selected experiments were predicted together with the 95% prediction interval. The predicted values and the associated prediction interval are based on the model developed previously. The predicted value and the actual experimental value were compared and the residual and the percentage error calculated. All these values were presented in Table 7. The percentage error range between the actual and predicted value for R_a and F_c are as follows: $R_a \sim -4.47$ to 7.76% and $F_c \sim -0.54$ to 2.16%.

Table 7
Confirmation experiments

No.	SCEA	Feed	Cutting speed	Surface roughness				Tangential force			
				Actual R_a	Predicted R_a	Residual	Error (%)	Actual F_c	Predicted F_c	Residual	Error (%)
1	−3	0.18	300	1.13	1.07	0.06	5.31	356.60	353.13	3.47	0.97
2	−3	0.23	375	2.06	1.98	0.08	3.88	440.78	431.26	9.52	2.16
3	−5	0.28	375	2.98	3.04	−0.06	−2.01	528.21	529.57	−1.37	−0.26
4	0	0.28	300	3.46	3.51	−0.05	−1.45	569.37	559.25	10.12	1.78
5	−3	0.18	375	1.16	1.07	0.09	7.76	343.56	345.42	−1.87	−0.54
6	−5	0.28	300	2.91	3.04	−0.13	−4.47	545.81	537.28	8.53	1.56

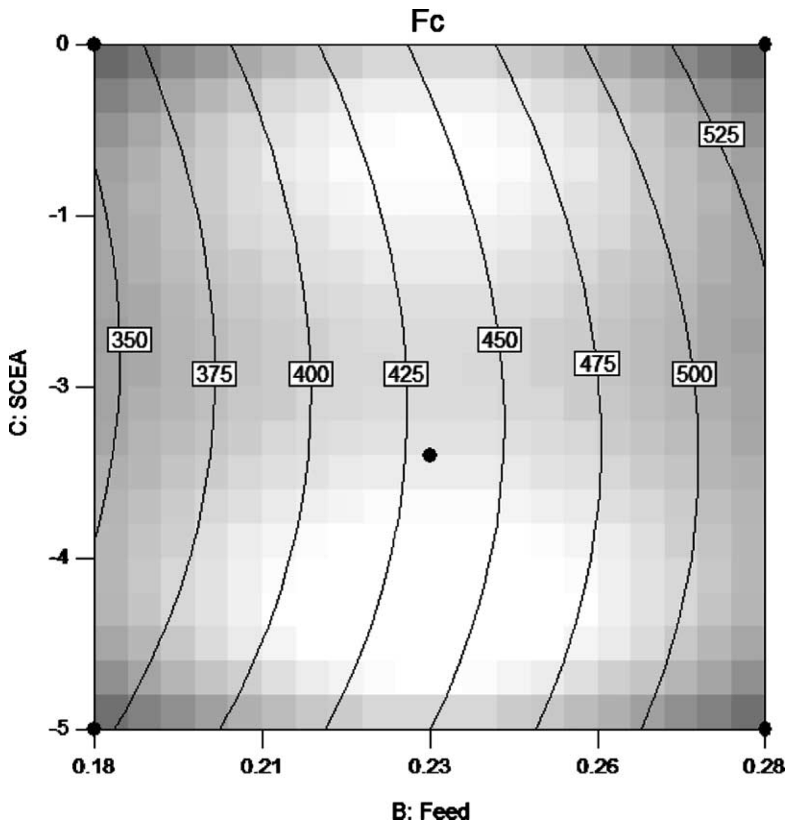

Fig. 10. Tangential force contours in feed–SCEA plane at cutting speed of 375 m/min.

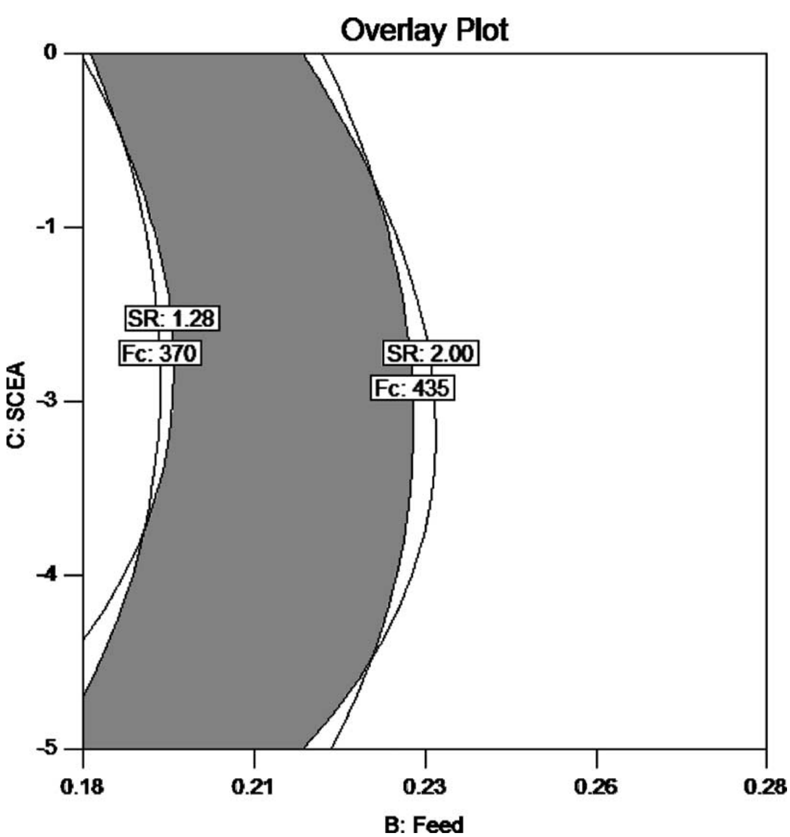

Fig. 11. Overlay plot.

It can be said that the empirical models developed were reasonably accurate, particularly for F_c. All the actual values for the confirmation run are within the 95% prediction interval. The 95% prediction interval is the range in which we can expect any individual value to fall into 95% of the time.

5. Conclusions

This paper presents the findings of an experimental investigation into the effect of feed rate, SCEA and cutting speed on the surface roughness and tangential force when turning AISI 1045 steel. The ANOVA revealed that feed is the most significant factor influencing the response variables investigated. The SCEA^2 and the feed and SCEA interaction factors provided secondary contribution to the responses investigated. Additionally, the cutting speed also provided secondary contribution to the tangential force. The reduced quadratic models developed using RSM were reasonably accurate and can be used for prediction within the limits of the factors investigated.

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References

[1] D.C. Montgomery, Design and Analysis of Experiments, 4th ed., Wiley, New York, 1997.
[2] M. Thomas, Y. Beauchamp, Y.A. Youssef, J. Masounave, An experimental design for surface roughness and built-up edge formation in lathe dry turning, Int. J. Qual. Sci. 2 (3) (1997) 167–180.
[3] W.H. Yang, Y.S. Tarng, Design optimization of cutting parameters for turning operations based on Taguchi method, J. Mater. Process. Technol. 84 (1998) 112–129.
[4] I.A. Choudhury, M.A. El-Baradie, Surface roughness prediction in the turning of high-strength steel by factorial design of experiments, J. Mater. Process. Technol. 67 (1997) 55–61.
[5] J.D. Thiele, S.N. Melkote, Effect of cutting edge geometry and workpiece hardness on surface generation in the finish hard turning of AISI 52100 steel, J. Mater. Process. Technol. 94 (1999) 216–226.
[6] C.Y. Nian, W.H. Yang, Y.S. Tarng, Optimization of turning operations with multiple performance characteristics, J. Mater. Process. Technol. 95 (1999) 90–96.
[7] B.Y. Lee, Y.S. Tarng, H.R. Lii, An investigation of modeling of the machining database in turning operations, J. Mater. Process. Technol. 105 (2000) 1–6.
[8] W.S. Lin, B.Y. Lee, C.L. Wu, Modeling the surface roughness and cutting force for turning, J. Mater. Process. Technol. 108 (2001) 286–293.
[9] R.A. Lindberg, Processes and Materials of Manufacture, 4th ed., Prentice-Hall, Englewood Cliffs, NJ, 1990.
[10] V.C. Venkatesh, I.A. Kattan, D. Hoy, C.T. Ye, J.S. Vankirk, An analysis of cutting tools with negative side cutting edge angles, J. Mater. Process. Technol. 58 (1996) 351–361.
[11] I.A. Kattan, Analytical and experimental investigations of the effect of a negative SCEA on machining parameters, Ph.D. Thesis, Tennessee Technological University, 1994.
[12] M.Y. Noordin, V.C. Venkatesh, C.W. Lok, S. Sharif, A. Abdullah, Performance evaluation of tool geometry of a multilayer tungsten carbide tool when turning AISI 1045 steel, in: V. Radhakrishnan, L. Vijayaraghavan, N. Ramesh Babu (Eds.), Proceedings of the 19th AIMTDR Conference, Mumbai, India, Narosa Publishing House, 2000, pp. 299–304.
[13] Design-Expert Software, Version 6, User's Guide, Technical Manual, Stat-Ease Inc., Minneapolis, MN, 2000.
[14] D.D. Steppan, J. Werner, R.P. Yeater, Essential regression and experimental design for chemists and engineers, 1998. http://geocities.com/SiliconValley/Network/1032/CGPage1.html.
[15] J. Wang, The effect of the multi-layer surface coating of carbide inserts on the cutting forces in turning operations, J. Mater. Process. Technol. 97 (2000) 114–119.
[16] M.Y. Noordin, V.C. Venkatesh, C.W. Lok, S. Sharif, A. Abdullah, Performance evaluation of cemented carbide tools in turning AISI 1010 steel, J. Mater. Process. Technol. 116 (2001) 16–21.
[17] D. Gillibrand, M. Sarwar, C.T. Pierce, The economic benefit of finish turning with coated carbide, Surf. Coat. Technol. 86–87 (1996) 809–813.
[18] A.G. Walter, Tungsten Carbide Tools General Catalogue, Trade Catalogue, Tübingen, 1996.
[19] E. Oberg, R.E. Green, Machinery's Handbook, 25th ed., Industrial Press Inc., New York, 1996.
[20] P.S. Sreejith, B.K.A. Ngoi, Dry machining: machining of the future, J. Mater. Process. Technol. 101 (2000) 287–291.
[21] Kennametal Inc., Steel Machining Catalog 9008, Trade Catalogue, USA, 1999.
[22] Kennametal Hertel, Kennametal Hertel News Catalogue, News I 2000, Trade Catalogue, Germany, 2000.
[23] E.J.A. Armarego, R.H. Brown, The Machining of Metals, Prentice-Hall, Englewood Cliffs, NJ, 1969.