PREDICTION OF TANGENTIAL CUTTING FORCE IN END MILLING OF MEDIUM CARBON STEEL BY COUPLING DESIGN OF EXPERIMENT AND RESPONSE SURFACE METHODOLOGY

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Abstract: *The present paper discusses the development of the first and second order models for predicting the tangential cutting force produced in end-milling operation of medium carbon steel. The mathematical model for the cutting force prediction has been developed, in terms of cutting parameters cutting speed, feed rate, and axial depth of cut using design of experiments and the response surface methodology (RSM). All the individual cutting parameters affect on cutting forces as well as their interaction are also investigated in this study. The second order equation shows, based on the variance analysis, that the most influential input parameter was the feed rate followed by axial depth of cut and, finally, by the cutting speed. Central composite design was employed in developing the cutting force models in relation to primary cutting parameters. 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 adequacy of the predictive model was verified using ANOVA at 95% confidence level. This paper presents an approach to predict cutting force model in end milling of medium carbon steel using coated TiN insert under dry conditions and full immersion cutting.*

Keywords: *Tangential Cutting Forces, RSM, coated TiN, model.*

INTRODUCTION

Peripheral milling is a widely used metal removal process in automobile, aerospace, textile machinery and other manufacturing industries for the roughing and finish cutting of profiled components, such as aircraft structural parts, dies and molds. Dynamic change in cutting force is one of the major sources causing the vibration in cutting process by which the machining accuracy will be deteriorated. Thus, accurate modeling of cutting forces is necessitated for the prediction of machining performance and to determine the mechanisms and machining parameters that affects the stability of machining operations. Due to the difficulty of measuring the length of shear line and to represent it as a function of measurable variables, the linear force model that is proportional to undeformed chip thickness is widely used in analysis and simulation [1-2]. Wilson et al. [3] developed a model of the orthogonal cutting process for wave removal and wave generation processes by which the result indicating the variation of shear angle and forces are directly related to the local surface slope of the generated wave has been obtained. Shin and Waters [4] also developed a model for face milling operation in which the machine tool structure, work-piece geometry and cutter geometry were taken into account. Presently developed cutting force models generally resort to the integrations of local cutting forces along the cutting flutes over cutter rotational cycles by numerical calculation [5-6], convolution analysis [7-8] and analytical formulation [9]. These models are obtained on condition of steady state cutting, in which the machining parameters are fixed. But in reality, variability in cutting parameters such as radial depth of cut is frequently encountered in applications such as die sinking or pocketing operations, where smaller-diameter end mills have to remove material, especially at corners, not removed by larger-diameter roughing end mills. The radial depth of cut generally varies due to the rough corner radius as the end mill enters the corner, which results in the changes of cutting forces. Many researchers focus on the cutting forces for the cases of varying machining conditions. Fussell and Srinivasan [10] investigate experimentally the cutting forces for the cases of changing axial and radial depths of cut and feed rate, as well as the startup transients in the force as the cutter engages with the work-piece. Li and Liang [11] predict the milling forces in the axial, feed and cross-feed directions during transient-state cutting as the cutter engages with and disengages from a work-piece. On the other hand, many other researchers have followed purely experimental approaches to study the relationship between cutting forces and independent cutting conditions.

This has reflected on the increased total cost of the study as a large number of cutting experiments is required. Furthermore, with this purely experimental approach, researchers have investigated the effect of cutting parameters on cutting forces using machining experiments based on a one-factor-at-a-time design, without having any idea about the behavior of cutting forces when two or more cutting factors are varied at the same time. The present study considers the effect of simultaneous variations of three cutting parameters (cutting speed, feed rate, and axial depth of cut) on the behavior of cutting forces. For this purpose, the response surface methodology RSM is utilized. RSM is a group of mathematical and statistical techniques that are useful for modeling the relationship between the input parameters (cutting conditions) and the output variable (cutting force) [12-13]. RSM saves cost and time on conducting metal cutting experiments by reducing the overall number of required tests. In addition, RSM helps describe and identify, with a great accuracy, the effect of the interactions of different independent variables on the response when they are varied simultaneously In this paper, the technique is used to develop a mathematical model that utilizes the response surface methodology and method of design experiments to predict the cutting force when milling medium carbon steel S45C using TiN coated Tungsten carbide inserts. The predicted cutting force results are presented in terms of mean values with 95% confidence interval.

RESPONSE SURFACE METHODOLOGY

RSM is a collection of mathematical and statistical techniques that are useful for the modeling and analysis of problems in which a response of interest is influenced by several variables and the objective is to optimize this response [14]. RSM also quantifies relationships among one or more measured responses and the vital input factors [15]. The version 6.0.8 of the Design Expert software [16] was used to develop the experimental plan for RSM. The same software was also used to analyze the data collected using the steps as follows:

- Choose a transformation if desired. Otherwise, leave the option at "None".
- 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.
- Perform the analysis of variance (ANOVA), post-ANOVA analysis of individual model coefficients and case statistics for analysis of residuals and outlier detection.
- Inspect various diagnostic plots to statistically validate the model.

If the model looks good, generate model graphs, i.e. the contour and 3D graphs, for interpretation. The analysis and inspection performed in steps stated 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 analyzing each response, multiple response optimization technique 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 analyzed 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 output 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 minimizing 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 tests are performed.

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.

Test for significance on individual model coefficients

This test forms the basis for model optimization 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.

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 in the earlier test, 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, observed 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 structure less, that is, they should contain no obvious patterns.

Mathematical Model

Cutting force model for end milling in terms of the parameters can be expressed in general terms as:

$$F_t = C\,V^k\,a^m f_z^l \qquad (1)$$

Where F_t is the predicted Cutting Force (N), V is the cutting speed (m/min), f_z is the feed per tooth (mm/tooth), and a is the axial depth of cut (mm). *C, k, l*, and *m* are model parameters to be estimated using the experimental results. To determine the constants and exponents, this mathematical model can be linearized by employing a logarithmic transformation, and Eq. (1) can be re-expressed as:

$$\ln F_t = \ln C + k \ln V + m \ln a + l \ln f \qquad (2)$$

The linear model of Eq. 2 is :

$$F_t = \beta_0 x_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 \qquad (3)$$

Where F_t is the true response of Cutting Force on a logarithmic scale, $x_0 = 1$ (dummy variable), x_1, x_2, x_3 are logarithmic transformations of speed, depth of cut, and feed, respectively, while β_0, β_1, β_2, and β_3 are the parameters to be estimated. Eq (3) can be expressed as

$$\hat{F}_t = F_t - \varepsilon = b_0 x_0 + b_1 x_1 + b_2 x_2 + b_3 x_3 \qquad (4)$$

Where $\hat{F}_t$ is the estimated response and F_t the measured Cutting Force on a logarithmic scale, ε the experimental error and the b_i values are estimates of the β_i parameters. The second-order model can be extended from the first-order model equation as:

$$\hat{F}_{2t} = F_t - \varepsilon = b_0x_0 + b_1x_1 + b_2x_2 + b_3x_3 + b_{11}x_1^2 + b_{22}x_2^2 + b_{33}x_3^2 + b_{12}x_1x_2 + b_{13}x_1x_3 + b_{23}x_2x_3 \qquad (5)$$

where, $\hat{F}_{2t}$ is the estimated response based on the second order model. Analysis of variance is used to verify and validate the model.

EXPERIMENTAL DETAILS

Experimental setup

Cutting tests was conducted mainly on Vertical Machining Center (VMC ZPS, Model: 1060) powered by a 30 KW motor with a maximum spindle speed of 8000 rpm. Fig.1 shows the experimental set up cutting test conditions on end milling for machining of medium carbon steel with TiN inserts. The computer software used was Kistler Dyno-Ware (type: 2825D1-2, version 2.31) which is universal and operator's friendly software. The cutting force equipments are shown in Fig.2.

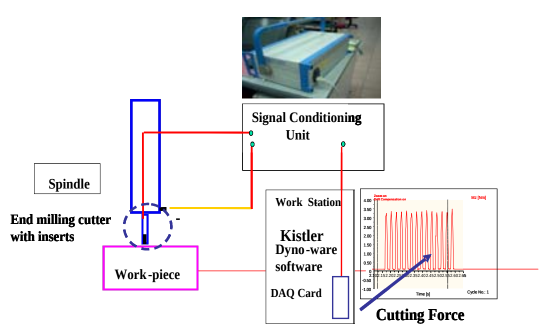

Fig.1 Experimental set up for end milling

The instrument can measure two components of cutting force i.e. Thrust for along z-axis (F_z) in Newton and Moment along z-axis (M_z) in Newton-meter. The Torque in z-axis M_z was then converted to Tangential force (F_t) by dividing it with the radius of the tool holder diameter as follows:

$$F_t = \frac{M_z}{Radius\_of\_tool\_HolderX0.001(m)}[N]$$

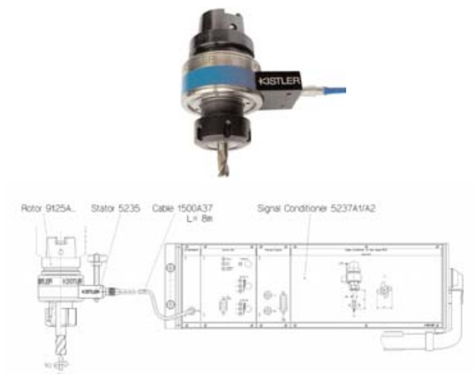

Fig.2 Cutting force Measurement Apparatus

Tool (inserts)

SANDVIK grade PM1030 Insert code: R390-11 T3 08E- PL, Insert coating material: carbide, Working condition: light to medium milling. For insert geometry refer to Fig. 3 and Table 1.

Table1 Insert Geometry Values

L	iW	d_1	s	b_s	r_ε	α_n°
11	6.8	2.8	3.59	1.2	0.8	21

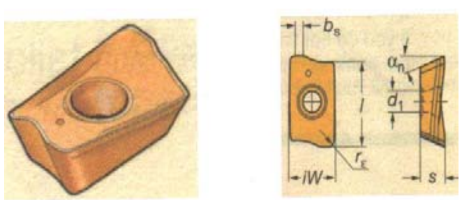

Fig. 3 Insert Shape and Geometry

Table 2 Coding Identification for end milling using Coated TiN cemented carbide inserts

Levels Coding	Lowest	Low	Centre	High	Highest
	$-\sqrt{2}$	-1	0	+1	$+\sqrt{2}$
x_1, cutting speed, *V* (m/min)	100	114.25	158	218.5	250
x_2, axial depth of cut, *a* (mm)	1.005	1.15	1.59	2.2	2.516
x_3, feed, f_z (mm/tooth)	0.039	0.05	0.089	0.16	0.204

Coding of the independent variables

The independent variables were coded taking into consideration the limitation and capacity of the cutting tools. Levels of independent and coding identification are presented in Table 2, for experiment using Coated TiN inserts, respectively.
The transforming equations for each of the independent variables are:

$$x_1 = \frac{\ln V - \ln 158}{\ln 218.5 - \ln 158};$$

$$x_2 = \frac{\ln a - \ln 1.59}{\ln 2.2 - \ln 1.59};$$

$$x_3 = \frac{\ln f_z - \ln 0.089}{\ln 0.16 - \ln 0.089}$$

The above relationships were obtained from the following transforming equation:

$$x_1 = \frac{\ln x_n - \ln x_{n0}}{\ln x_{n1} - \ln x_{n0}}$$

Where, x is the coded value of any factor corresponding to its natural value x_n. x_{n1} is the +1 level and x_{n0} is the natural value of the factor corresponding to the base of zero level.

Experimental Design

The design of the experiments has an effect on the number of experiments required. Therefore, it is important to have a well-designed experiment to minimize the number of experiments which often are carried out randomly. Cutting conditions in coded factors and the cutting force values obtained using TiN coated cemented carbide insert are presented in Table 3.

Table 3 Cutting force results and cutting conditions in coded factors

No.	Type	Coding of Level			Cutting Forces (N)
		x1 Cutting speed,	x2 Axial Depth of cut	x3 Feed,	
		m/min	mm	mm/ tooth	
1	Factorial	1	1	-1	400
2	Factorial	1	-1	1	530
3	Factorial	-1	1	1	925
4	Factorial	-1	-1	-1	360
5	Centre	0	0	0	570
6	Centre	0	0	0	570
7	Centre	0	0	0	568
8	Centre	0	0	0	569
9	Centre	0	0	0	568
10	Axial	-1.414	0	0	550
11	Axial	1.414	0	0	470
12	Axial	0	-1.414	0	380
13	Axial	0	1.414	0	610
14	Axial	0	0	-1.414	405
15	Axial	0	0	1.414	840

Table 4 ANVOA of cutting performance in terms of cutting forces

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	3	0.92	0.31	42.33	<0.0001
Error	4	1.235E-005	3.089E-006		
C Total	14	0.99			
Std. Dev	Mean	R-square	Adj R-sq	C.V.	Adeq Precision
0.085	6.28	0.9270	0.9051	1.35	19.850

Table 5 Fit and Summary test of the second order CCD model

Sequential Model Sum of Squares						
Source	Sum of Squares	DF	Mean Square	F Value	Prob > F	
Mean	592.24	1	592.24			
Block	6.061E-003	1	6.061E-003			
Linear	**0.92**	**3**	**0.31**	**42.33**	**<0.0001**	**Suggested**
2FI	0.011	3	3.751E-003	0.43	0.7368	
Quadratic	**0.061**	**3**	**0.020**	**6559.91**	**<0.0001**	**Suggested**
Cubic	0.000	0				Aliased
Residual	1.235E-005	4	3.089E-006			
Total	593.24	15	39.55			

Table 6 ANOVA for second order CCD model

ANOVA for Response Surface Reduced Quadratic Model						
Source	Sum of Squares	DF	Mean Square	F Value	Prob > F	
Block	6.061E-003	1	6.061E-003			
Model	0.99	8	0.12	33217.37	<0.0001	Significant
x_1	0.012	1	0.012	3325.83	<0.0001	
x_2	0.22	1	0.22	59671.47	<0.0001	
x_3	0.27	1	0.27	71637.88	<0.0001	
x_1^2	0.016	1	0.016	4411.29	<0.0001	
x_2^2	0.041	1	0.041	11055.72	<0.0001	
x_3^2	3.603E-003	1	3.603E-003	970.01	<0.0001	
$x_1 x_2$	4.676E-003	1	4.676E-003	1258.88	<0.0001	
$x_2 x_3$	6.570E-003	1	6.570E-003	1768.80	<0.0001	
Residual	1.857E-005	5	3.714E-006			
Lack of Fit	6.217E-006	1	6.217E-006	2.01	0.2290	not significant
Pure Error	1.235E-005	4	3.089E-006			
Cor Total	0.99	14				

In the experiment, small central composite design was used to develop the cutting force model. The analysis of mathematical models was carried out using Design-expert 6.0 package.

RESULTS AND DISCUSSIONS

Development first order model using small CCD design

From the experimental results, empirical equations were developed to predict the cutting force and the significant parameters involved. Table 4 show the ANVOA and parameter estimates of cutting performance in terms of cutting force. The first order model obtained from the experimental data in Table 2 is as follows:

$$\hat{y}_1 = 6.28 - 0.084x_1 + 0.17x_2 + 0.28x_3 \quad (6)$$

The cutting force contours of experimental and linear calculated values show some variations (Fig.4). The analysis of variance (ANOVA) of linear CCD is shown in Table 4 above. It is observed from the ANOVA that the "Model F-Value" of 42.33 implies that the model is significant. The lack of fit is significant. There is a change that a "Lack of Fit F-value" this large occurs due to noise.

Development of second order model using CCD design

The Fit and summary test which are shown in Table 5, indicate that the quadratic model CCD models was more significant than linear model and it also proved that linear model has a significant lack of fit (LOF). Therefore, the quadratic model was chosen in order to develop the CCD model. The second order cutting force model is given as:

$$\hat{y}_2 = 6.33 - 0.056x_1 + 0.17x_2 + 0.26x_3 - 0.047x_1^2 - 0.074x_2^2 + 0.022x_3^2 - 0.048x_1x_2 + 0.057x_2x_3 \quad (7)$$

To verify the adequacy of the proposed second order CCD model, ANOVA was used and the results are shown in the Table 6. The quadratic CCD model shows that feed has the most significant effect on cutting force, followed by axial depth of cut and cutting speed. The interaction effects between the cutting parameters also give a significant effect on cutting force values.

Fig. 4 indicates the contours of actual cutting force values and the corresponding predicted values of quadratic CCD models. The graphs indicated that the quadratic model could predict cutting force values very close to the actual values. It can be also observed from Fig.4 that quadratic model leads to the values more close to the actual values compared to linear model. Fig 5 shows the 3D-response surface of quadratic CCD model based on the effect of speed and depth of cut on cutting force and depth of cut and feed on cutting force. The contours affirm that cutting force can be affected by the feed followed by axial depth of cut and cutting speed. The normal probability plots of the residuals and the plots of the residuals versus the predicted response for cutting force are shown in Fig.6, Fig. 7 respectively. A check on the plots in Fig.6 revealed that the residuals generally fall on a straight line implying that the errors are distributed normally.

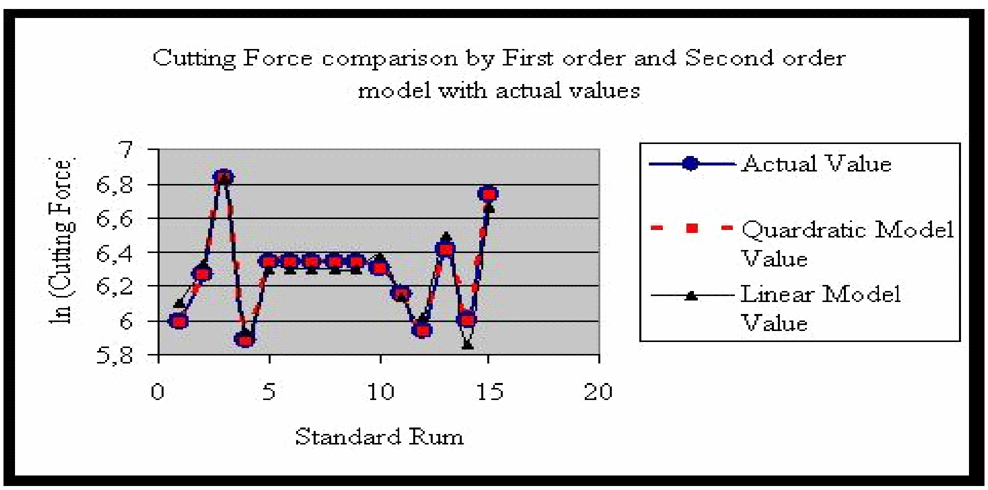

Fig 4 Cutting force contours of experimental and quadratic CCD predicted values

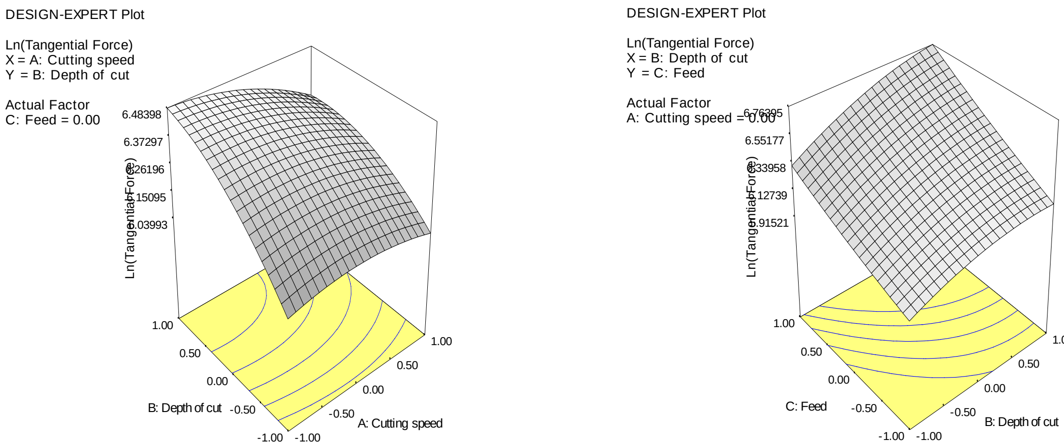

Fig 5 The response surface of the quadratic CCD model for end milling using coated TiN insert

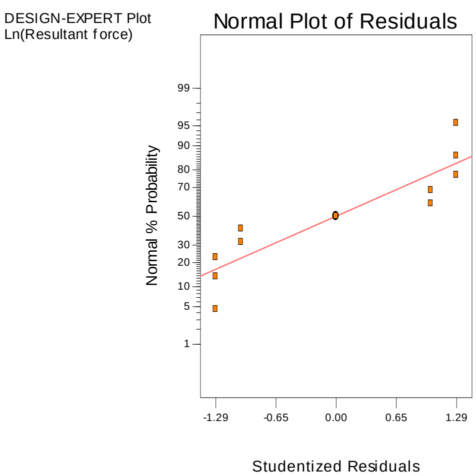

Fig 6 Normal probability plot of residuals for F_a data

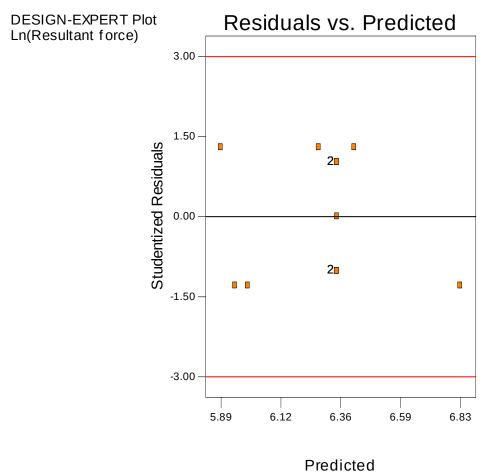

Fig 7 Plot of residuals vs. predicted response for F_a data.

Also Fig7 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.

Effect of cutting speed on tangential Cutting Force

By analysis the developed quadratic model, it has been also observed that with the increase of cutting speed the tangential cutting force decreases as shown in Fig 8. It has been also observed that at high depth of cut the cutting force is high but it also follow the similar tendency as low depth of cut.

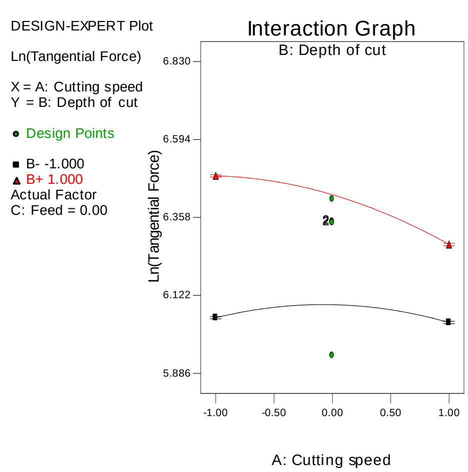

Fig.8: Effect of Tangential Cutting force on Cutting speed at different depth of cut

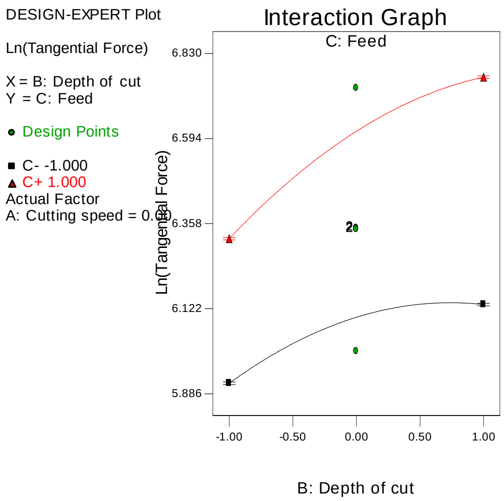

Fig.9: Effect of Tangential Cutting force on Depth of cut at different Feed

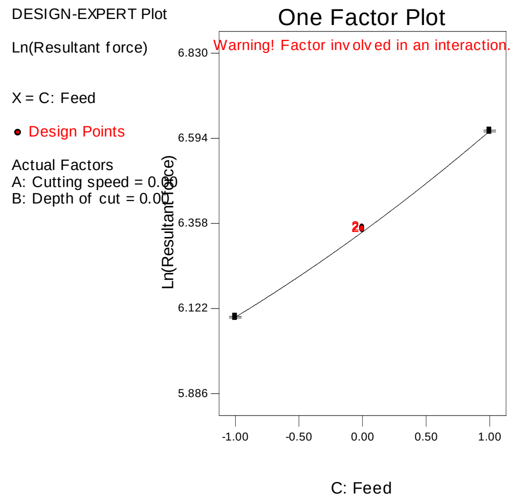

Fig.10: Effect of Tangential Cutting force on Feed

Effect of Depth of cut on Tangential Cutting Force

By analysis the developed quadratic model, it has been also observed that with the increase of depth of cut the tangential cutting force increases as shown in Fig 9. At high feed the tangential cutting force increase higher than that of low feed.

Effect of Feed on Tangential Cutting Force

By analysis the developed quadratic model, it has been also observed that with the increase of feed the tangential cutting force increases significantly as shown in Fig. 10.

Fig 11 shows the overall cutting parameters effect on tangential cutting force presented by a cube graph. It has been observed that feed is the most significant parameters followed by depth of cut and cutting speed for the tangential cutting force. Both the feed and depth of cut has the positive effect whereas cutting speed has the negative effect on tangential cutting force.

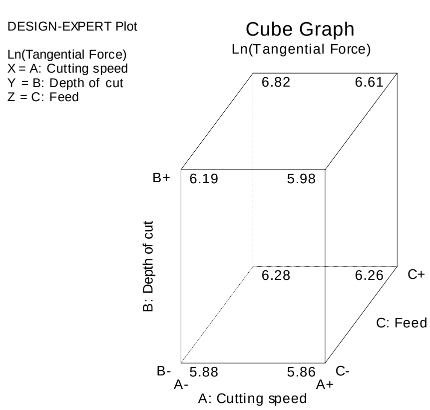

Fig.11: Effect of Tangential Cutting force on different cutting parameters

CONCLUSIONS

This research paper discussed the development of a theoretical and experimental model for improving the efficiency of face milling of medium carbon steel (S45C) using coated TiN inserts. The general conclusions can be summarized as follows:

The two models (linear and quadratic CCD) indicate that the feed was the most significant influence on tangential cutting force, followed by depth of cut and cutting speed

An increase in either the feed or the axial depth of cut increases the cutting force, whilst an increase in the cutting speed decreases the cutting force.

Contours of surface outputs are constructed in planes containing two of the independent variables. These contours were further developed to enable the selection on the proper combination of cutting parameters to increase the metal removal rate without sacrificing the quality of the surface finish produced.

The CCD model developed by RSM using Design Expert package is able to provide accurately the predicted values of cutting force close to actual values found in the experiments. The equations are checked for their adequacy with a confidence level of 95%.

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