European Journal of Scientific Research
ISSN 1450-216X Vol.21 No.4(2008), pp.592-602

http://www.eurojournals.com/ejsr.htm

Prediction of Tool Life in End Milling of Hardened Steel AISI D2

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Abstract

Most published research works on the development of tool life model in machining of hardened steels have been mainly concerned with the turning process, whilst the milling process has received little attention due to the complexity of the process. Thus, the aim of present study is to develope a tool life model in end milling of hardened steel AISI D2 using PVD TiAlN coated carbide cutting tool. The hardness of AISI D2 tool lies within the range of 56-58 HRC. The independent variables or the primary machining parameters selected for this experiment were the cutting speed, feed, and depth of cut. First and second order models were developed using Response Surface Methodology (RSM). Experiments were conducted within specified ranges of the parameters. Design-Expert 6.0 software was used to develop the tool life equations as the predictive models. The predicted tool life results are presented in terms of both 1^{st} and 2^{nd} order equations with the aid of a statistical design of experiment software called Design-Expert version 6.0. Analysis of variance (ANOVA) has indicated that both models are valid in predicting the tool life of the part machined under specified condition and the prediction of average error is less than 10%.

Keywords: Hardened steel, Tool life, Response surface methodology (RSM), hard milling

1. Introduction

Machining hardened steel parts has become more pronounce in manufacturing process, particularly in the mold and die industries and subsequently mostly contributed in making automotive and aerospace components. Due to the hardness of the material, abrasive processes such as grinding, polishing, etc. have been typically required, but advances in machine tool and cutting tool materials has allowed machining of hardened steels to become a realistic replacement for many grinding applications.

Despite of having outstanding machinery, no one could not expect the failure of tool life for certain conditions in machining operation. It will become most apparent when machining hard materials such as hardened steel. Thus, how to find the best way to prolong the life of a tool subjected to hardened material cutting is the aim of this study.

Tool wear/tool life is an important aspect commonly considered in evaluating the performance of a machining process. In addition, tool wear/tool life estimates and the corresponding economic analysis are among the most important topics in process planning and machining optimization (Ee et al., 2006). Plus tool life prediction is an important factor that has profound influence on the higher productivity in industrial activities. High metal removal rate is intended to reduce the manufacturing cost and operation time. The productivity interms of a machining operation and machining cost, as well as quality assurance, and the quality of the workpiece machined surface and its integrity are strongly depend on tool wear and consequently it depends on the life of the tool. Moreover, despite having the target of achieving optimum superficial finishing with the shortest possible time one must take into account the consideration of tool life, so that the complete finishing operation can be carried out with just one tool, avoiding the intermediate stops in order to change the tool due to its wear (Lopez de Lacalle et al., 2007). Eventually, sudden failure of cutting tools lead to loss of productivity, rejection of parts and consequential economic losses (Palanisamy et al., 2007).

Selection of cutting tools and cutting conditions represents an essential element in process planning for machining. This task is traditionally carried out on the basis of the experience of process planners with the help of data from machining handbooks and tool catalogs. Process planners continue to experience great difficulties due to lack of performance data on the numerous new commercial cutting tools with different materials, coatings, geometry and chip-groove configurations for high wear resistance and effective chip breaking, etc. (Jawahir & Wang, 2007). Moreover, specific data on relevant machining performance measures such as tool-life, surface roughness, chatter&vibration, chip formation, and cutting forces are hard to find due to lack of predictive models for these measures. Therefore, it is indispensable to predict tool life under varying cutting conditions and it becomes main issue towards this study. In order to establish the knowledge base for tool life, a large number of experiments have to be performed and analysed. However, it is well known that obtaining reliable machining data is very costly in terms of time and material (Tsai et al., 2005). Thus, various methodologies and strategies have been adopted by researchers in order to predict tool life in milling and turning. Four major categories were created to classify the methodologies. These are: (i) approaches that are based on machining theory to develop analytical models and/or computer algorithms to represent the machined surface; (ii) approaches that examine the effects of various factors through the execution of experiments and analysis of the results; (iii) approaches that use designed experiments; and (iv) the artificial intelligence (AI) approaches (Benardos & Vosniakos 2003).

Response surface methodology (RSM) which is classified into designed experiments approach seems to be the most wide-spread methodology for the tool life prediction. RSM is an important methodology used in developing new processes, optimizing their performance, and improving the design and/or formulation of new products. It is often an important concurrent engineering tool in which product design, process development, quality, manufacturing engineering, and operations personnel often work together in a team environment to apply RSM. It is a dynamic and foremost important tool of design of experiment (DOE), wherein the relationship between responses of a process with its input decision variables is mapped to achieve the objective of maximization or minimization of the response properties (Raymond & Douglas 2002).

Many researchers have used RSM for their experimental design and analysis of the results in end milling, but very few of them were engaged in machining hard material which is commonly known as hard milling. Vivancos et. al. (2005) presented a model for the prediction of surface roughness in high-speed side milling of hardened die steels. Palanisamy et al. (2007) predicted the response variable tool wear based on DOE combined with RSM technique in a universal milling machine on AISI 1020 steel using carbide insert. The development of a surface roughness model for end milling EN32 casehardening carbon steel (160 BHN steel) using design of experiments and RSM was discussed by Mansor & Abdalla (2002).

In this paper, the RSM has been applied to develop a mathematical model to predict the tool life for end milling of hardened steel AISI D2 tool steel which is categorized as a difficult to cut material. Machining was conducted using PVD TiAlN carbide coated SANDVIK 1030 inserts. The accuracy of the model has been tested using the analysis of variance (ANOVA) with the aid of a statistical design of experiment software called Design-Expert version 6.0. Knowledge of tool life will help the process planner or operator in selecting the optimum parameters to minimize the tool wear.

2. Mathematical Model by RSM

The relationship between tool life and other independent variables is modelled as follows;

$$TL = CV^{k} d^{l} f^{m} \tag{1}$$

Where 'C' is a model constant and 'k', 'l' and 'm' are model parameters. The above function (1) can be represented in linear mathematical form as follows;

$$\ln(TL) = \ln C + k\ln V + l\ln d + m\ln f \tag{2}$$

the first-order linear model of the above Eq. (2) can be represented as follows;

$$\hat{y}_1 = y - \varepsilon = b_0x_0 + b_1x_1 + b_2x_2 + b_3x_3 \tag{3}$$

Where, $\hat{y}_1$ is the estimated response based on first-order equation and y is the measured tool life on a logarithmic scale, $x_0 = 1$ (dummy variable), x_1, x_2, x_3 are logarithmic transformations of cutting speed, depth of cut and feed respectively. The parameters b_0, b_1, b_2, and b_3 are to be estimated where ε the experimental error. The second-order model can be extended from the first-order equation as follows;

$$\begin{aligned}\hat{y}_2 &= y - \varepsilon = b_0x_0 + b_1x_1 + b_2x_2 + b_3x_3 + b_{11}x_1^2 + b_{22}x_2^2 \\ &+ b_{33}x_3^2 + b_{12}x_1x_2 + b_{13}x_1x_3 + b_{23}x_2x_3\end{aligned} \tag{4}$$

Where, $\hat{y}_2$ is the estimated response based on the second-order model. Analysis of variance (ANOVA) is used to verify and validate the model.

3. Experimental Design and Methodology

Experimental works were carried out on CNC Vertical Milling Center (VMC) Excell PMC-10T24 with 40 mm diameter tool holder. End milling operation was performed under dry cutting conditions with a 5 mm constant radial depth of cut. Down milling method was employed to secure the advantageous outcomes such as better surface finish, less heat generation, larger tool life, better geometrical accuracy and compressive stresses favorable for carbide edges (Li et al., 2006). In this experiment only one insert was used for each set of experimental conditions so that the variation due to the wear of cutting tool edge is minimized among the trials. Machining was implemented with initially a sharp insert and moved every 100 mm pass of cut for flank wear measurement by Olympus Tool Maker microscope for which flank wear was recorded at 20 times magnification. Flank wear have been measured for each combination of cutting conditions in accordance with the ISO standard for tool life testing of end milling (ISO Standard 8688-2, 1989).

The cutting conditions were selected by considering the recommendations of the cutting tool's manufacturer (Sandvik Tools) and the knowledge of practices, gathered through contemporary literatures on hard machining. The three main selected parameters: cutting speed, depth of cut and feed were then coded to the levels using the following transformations;

$$X_1 = \frac{\ln V - \ln 56.57}{\ln 72.28 - \ln 56.57}; X_2 = \frac{\ln d - \ln 1.00}{\ln 1.63 - \ln 1.00}; X_3 = \frac{\ln f - \ln 0.044}{\ln 0.079 - \ln 0.044} \tag{5}$$

The independent variables with their corresponding selected levels of variation and coding identification are presented in Table 1.

Table 1: Independent variables with levels and coding identification

Indep. Variables	**Levels in Coded Form**				
	-√2 (lowest)	**-1 (low)**	**0 (centre)**	**+1 (high)**	**+√2 (highest)**
Cutting speed (V) (m/min) (X_1)	40	44.27	56.57	72.28	80
Depth of cut (d) (mm) (X_2)	0.50	0.61	1.00	1.63	2.00
Feed (F) (mm/tooth) (X_3)	0.02	0.025	0.044	0.079	0.10

A well-planned design of experiment can substantially reduce the number of experiments and for this reason a small CCD with five levels was selected to develop the first order and second order models. This is the most popular class of designs used for fitting these models and has been established as a very efficient design for fitting the second order model (Douglas, 2005). The analysis of mathematical models was carried out using Design Expert version 6.0 package for both the first and second order models. The machining process carried out in random manner in order to reduce error due to noise. The overall cutting conditions with CCD is presented in Table 2.

Table 2: Design Cutting Conditions with CCD

Trial no. (T)	**Location in CCD**	**Coded Form**			**Actual Form**		
		X_1	**X_2**	**X_3**	**Cutting speed (m/min)**	**Depth of cut (mm)**	**feed (mm/tooth)**
1	Factorial	+1	+1	-1	72.28	1.63	0.025
2	Factorial	+1	-1	+1	72.28	0.61	0.079
3	Factorial	-1	+1	+1	44.27	1.63	0.079
4	Factorial	-1	-1	-1	44.27	0.61	0.025
5	Center	0	0	0	56.57	1.00	0.044
6	Center	0	0	0	56.57	1.00	0.044
7	Center	0	0	0	56.57	1.00	0.044
8	Center	0	0	0	56.57	1.00	0.044
9	Center	0	0	0	56.57	1.00	0.044
10	Axial	-1.414	0	0	40.00	1.00	0.044
11	Axial	+1.414	0	0	80.00	1.00	0.044
12	Axial	0	-1.414	0	56.57	0.50	0.044
13	Axial	0	+1.414	0	56.57	2.00	0.044
14	Axial	0	0	-1.414	56.57	1.00	0.020
15	Axial	0	0	+1.414	56.57	1.00	0.100

4. Results and Discussion

The tool life values (response) and the other values that correspond to the tool life have been presented in Table 3.

Table 3: Measured Values and Responses

Trial no. (T)	Actual Form			Measured Values			Response
	Cutting speed (m/min)	Depth of cut (mm)	feed (mm/tooth)	Feed rate (mm/min)	Length of cut (mm)	Toolwear VB_{max}. =0.3mm	Tool life (TL) (min)
1	72.28	1.63	0.025	14.38	400	0.307	27.83
2	72.28	0.61	0.079	45.43	400	0.299	8.81
3	44.27	1.63	0.079	27.82	700	0.303	25.16
4	44.27	0.61	0.025	8.80	1100	0.292	124.93
5	56.57	1.00	0.044	19.80	600	0.367	30.30
6	56.57	1.00	0.044	19.80	600	0.353	30.30
7	56.57	1.00	0.044	19.80	600	0.363	30.30
8	56.57	1.00	0.044	19.80	600	0.359	30.30
9	56.57	1.00	0.044	19.80	600	0.361	30.30
10	40.00	1.00	0.044	14.00	1600	0.297	114.27
11	80.00	1.00	0.044	28.00	300	0.314	10.71
12	56.57	0.50	0.044	19.80	1400	0.301	70.70
13	56.57	2.00	0.044	19.80	400	0.343	20.20
14	56.57	1.00	0.02	9.00	500	0.302	55.55
15	56.57	1.00	0.10	45.00	400	0.453	8.89

4.1. Development of First & Second Order Models by ANOVA

Using the experimental results as obtained in the form of tool life values against all the set experimental conditions and followed by ANOVA analogy, the following tool life prediction model has been developed;

$$\ln(TL) = 3.36 - 0.74 \ln X_1 + 0.28 X_2 + 0.79 X_3 \qquad (6)$$

This is a first order model. By substituting Eq.(5) into Eq.(6), the model finally can be expressed as;

$$TL = 167711\, V^{-3.02}\, d^{-0.57}\, f^{-1.14} \qquad (7)$$

From this 1st order model (Eq.7) it is apparent that higher cutting speed will lower the tool life values followed by feed and depth of cut. This equation is valid for cutting speed ($40 \le V \le 80$), depth of cut ($0.5 \le d \le 2$) and feed ($0.02 \le f \le 0.1$). Since the second-order model is very flexible, easy to estimate the parameters with method of least square error, and work well in solving real response surface problems (Raymond & Douglas 2002), the analysis was extended in prediction of more robust modeling of tool life. Using the experimental data in Table 3, the second order model is derived with the following equation;

$$Ln(TL) = 3.462 - 0.837X_1 - 0.443X_2 - 0.668X_3 + 0.09X_2^2 - 0.175X_3^2 - 0.329X_1X_3 - 0.199X_2X_3 \qquad (8)$$

Or by conversion of inverse logarithm we could simplify the eq.(8) as such below;

$$TL = e^{Ln(TL)} \qquad (9)$$

This model takes into account of the interaction and quadratic effects of the cutting variables. Both Eq. (7) and (8) representing 1st and 2nd order CCD models respectively have indicated that cutting speed would give significant effect on tool life values followed by feed and depth of cut. Tool wear tends to increase with increasing cutting speed. It has been reported by Eldem & Barrow (1976) that increase in cutting speed accelarates thermally activated wear mechanisms in addition to generating more intense mechanical impact. These promote an increase in the thermal gradient which tends to increase too wear as thermal crack generation rate increases (Bhatia et al., 1979). Similar trends were also reported by Ping & Yeong (1997) and Shaw (1991). Plus similar phenomena were also founded by Vivancos et al. (2005), Ghani et al. (2004), Ghani et al. (2004a), Becze et al. (2000) when machining hardened steel at higher cutting speed. According to previously research reported by Shaw (1991), the high hardness will enhance too wear, and the content of the constituents C and Cr in hardened steels will give rise to hard particles in the workpiece, and increase the wear of the tool. Furthermore, because the longer time contact position (high cutting speed) between the tool and workpiece will cause high temperature in the cutting zone, the constituents C,Cr and Ni will harden the workpiece, and then tool life will be reduced. Thus, the tendency of tool wear to increase with increasing cutting is found to be predominant. These effects are further explained with the help of response surface plots as shown in Figs. 1 and 2. It is evident from the contour surface that tool life is maximum (125 min) when cutting speed (V=40m/min) and feed rate (f=0.027mm/tooth) at the lower limit (<-1.00).

Figure 1: Contour plot on 2-D contour RSM response surface plot with the optimization area of tool life (TL) [Design point: TL=4.83@125min, V=-1.00@40m/min, d=-1.00@0.6m/min, f=0.83@0.027mm/tooth]

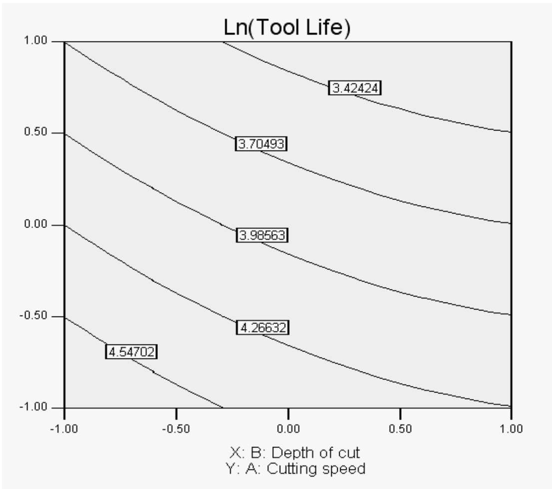
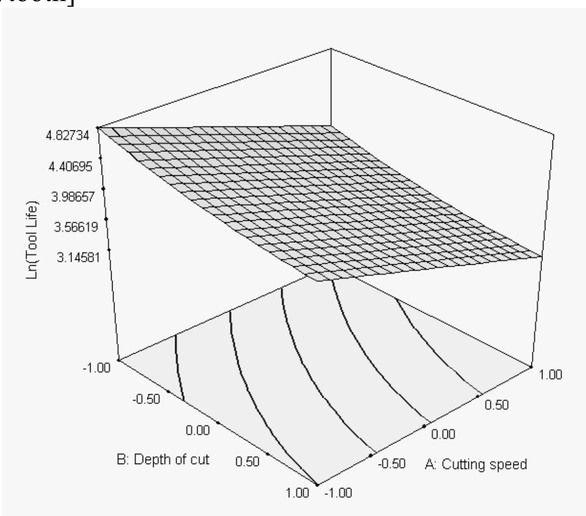


Figure 2: Contour plot on 3-D contour RSM response surface plot with the maximum and minimum values of tool life (TL) [Design point: TL=4.83@125min, V=-1.00@40m/min, d=-1.00@0.6m/min, f=0.83@0.027mm/tooth]



4.2. Checking the adequacy of the developed model

The accuracy of both models (linear and quadratic) has been tested using the analysis of variance technique (ANOVA) (Douglas, 2005; Raymond & Douglas, 2002) and with the aid of computer system simulation called Design Expert System version 6.0.

4.2.1. Checking the adequacy of the linear model

From Table 4 below, the Model F-value of 45.13 implies the model is significant. There is only a 0.01% chance that a "Model F-Value" this large could occur due to noise. Values of "Prob > F" less than 0.0500 indicate model terms are significant. In this case V, d, f are significant model terms. Values greater than 0.1000 indicate the model terms are not significant. If there are many insignificant model terms (not counting those required to support hierarchy), model reduction may improve your model. The "Pred R-Squared" of 0.7840 is in reasonable agreement with the "Adj R-Squared" of 0.9106. "Adeq Precision" measures the signal to noise ratio. A ratio greater than 4 is desirable. Your ratio of 19.388 indicates an adequate signal. The "Lack of Fit F-value" of 0.30 implies the Lack of Fit is not significant relative to the pure error. There is a 82.66% chance that a "Lack of Fit F-value" this large could occur due to noise. Non-significant lack of fit is good -- we want the model to fit.

Table 4: ANOVA of 1st order (linear) CCD Model

ANOVA for Response Surface Linear Model						
Analysis of Variance Table [Partial sum of squares]						
Source	**Sum of Squares**	**DF**	**Mean Square**	**F Value**	**Prob > F**	**Signifinicant or not significant**
Block	2.853E-003	1	2.853E-003			
Model	8.54	3	2.85	45.13	< 0.0001	Significant
V	4.35	1	4.35	68.98	< 0.0001	
d	0.62	1	0.62	9.80	0.0107	
f	3.57	1	3.57	56.61	< 0.0001	
Residual	0.63	10	0.063			
Lack of Fit	0.1134	6	0.0189	0.30	0.8266	Not significant
Pure error	0.18	4	0.045			
Adj R-Squared = 0.9106		Pred R-Squared = 0.784		R = 0.885		Adeq Precision = 19.388

4.2.2. Checking the adequacy of the quadratic model

The Model F-value of 299.22 implies the model is significant. There is only a 0.01% chance that a "Model F-Value" this large could occur due to noise. Values of "Prob > F" less than 0.0500 indicate model terms are significant. In this case V, d, f, d^2, f^2, Vf, df are significant model terms. Values greater than 0.1000 indicate the model terms are not significant. If there are many insignificant model terms (not counting those required to support hierarchy), model reduction may improve your model. The "Pred R-Squared" of 0.8523 is in reasonable agreement with the "Adj R-Squared" of 0.9938. "Adeq Precision" measures the signal to noise ratio. A ratio greater than 4 is desirable. Your ratio of 51.031 indicates an adequate signal. The "Lack of Fit F-value" of 0.21 implies the Lack of Fit is not significant relative to the pure error. There is a 65.13% chance that a "Lack of Fit F-value" this large could occur due to noise. Non-significant lack of fit is good -- we want the model to fit.

Table 5: ANOVA of 2st order (Quadratic) CCD Model

ANOVA for Response Surface Quadratic Model						
Analysis of Variance Table [Partial sum of squares]						
Source	**Sumof Squares**	**DF**	**Mean Square**	**F Value**	**Prob > F**	**Signifinicant or not significant**
Block	2.853E-003	1	2.853E-003			
Model	9.14	7	1.31	299.22	< 0.0001	significant
V	2.80	1	2.80	642.01	< 0.0001	
d	0.78	1	0.78	179.78	< 0.0001	
f	3.57	1	3.57	817.88	< 0.0001	
d^2	0.062	1	0.062	14.11	0.0094	
f^2	0.23	1	0.23	52.85	0.0003	
Vf	0.22	1	0.22	49.85	0.0004	
df	0.079	1	0.079	18.19	0.0053	
Residual	0.026	6	4.365E-003			
Lack of Fit	1.833E-003	2	9.166E-004	0.21	0.6513	Not significant
Pure error	0.071					
Adj -Squared = 0.9938		Pred R-quared = 0.8523		R = 0.923		Adeq Precision = 51.031

4.3. Checking the estimated of error of the developed model

Table 6 shows the values of tool life for experimental, predicted by linear and quadratic models, and error terms. From the table, it is clear that the error of quadratic model is much less than the error of linear model for which the average error of quadratic model given by the eq. 12 is only 0.04. For average error of linear model which has been calculated by the eq.10 is 0.08. As has been seen here the error of linear model is almost twice to the quadratic model. It is thus clear that the quadratic model is much reliable in predicting the tool life model with CCD design. Additionally, it is revealed that CCD design has been established as a very efficient design for fitting the second order model (Douglas, 2005). To the extent possible, for each model, we shall calculate the standard deviation that has been demonstrated in eqs. 11 and 13. The value of standard deviation for quadratic model which is 0.028 compared with linear model 0.183 is remarkably much smaller. These results provided insight for predicting tool life modelling and as well as the optimization.

Table 6: Experimental, Predicted and Error Values

Trial no. (T)	Design cutting condition			Response=Tool life (TL)(min)			Error (ei)	
	Cutting speed (m/min)	Depth of cut (mm)	Feed (mm/tooth)	Experim. values	Predicted value Linear	Predicted value Quadratic	Linear model	Quadratic model
1	72.28	1.63	0.025	27.83	20.69	26.05	0.26	0.06
2	72.28	0.61	0.079	8.81	9.76	9.03	-0.11	-0.03
3	44.27	1.63	0.079	25.16	24.49	25.47	0.03	-0.01
4	44.27	0.61	0.025	124.93	159.23	122.83	-0.27	0.02
5	56.57	1.00	0.044	30.30	30.08	31.88	0.01	-0.05
6	56.57	1.00	0.044	30.30	30.08	31.88	0.01	-0.05
7	56.57	1.00	0.044	30.30	30.08	31.88	0.01	-0.05
8	56.57	1.00	0.044	30.30	30.08	31.88	0.01	-0.05
9	56.57	1.00	0.044	30.30	30.08	31.88	0.01	-0.05
10	40.00	1.00	0.044	114.27	85.67	104.18	0.25	0.09
11	80.00	1.00	0.044	10.71	10.56	9.76	0.01	0.09
12	56.57	0.50	0.044	70.70	44.65	71.72	0.37	-0.01
13	56.57	2.00	0.044	20.20	20.26	20.37	0.00	-0.01
14	56.57	1.00	0.02	55.55	73.89	57.00	-0.33	-0.03
15	56.57	1.00	0.10	8.89	11.80	8.92	-0.33	0.00

Average of error (linear),

$$Avg_{el} = \frac{\sum_{i=1}^{15} \left| Sum\ of\ error\ of\ linear\ (e_l) \right|}{\sum_{i=1}^{15} Total\ number\ of\ trial\ (T)} \tag{10}$$

$$Avg_{el} = \frac{\left| 0.26 + 0.11 + ... + 0.33 \right|}{15}$$

$$= 0.08$$

Standard deviation (linear),

$$Std_l = \sqrt{\frac{\sum_{i=1}^{15} (each\ trial\ of\ linear\ error - average\ of\ linear\ error)}{\sum No.of\ trial\ (T) - 1}} \tag{11}$$

$$= 0.183$$

Average of error (quadratic),

$$Avg_{eq} = \frac{\sum_{i=1}^{15} \left| Sum\ of\ error\ of\ quadratic\ (e_q) \right|}{\sum_{i=1}^{15} Total\ number\ of\ trial\ (T)} \tag{12}$$

$$Avg_{eq} = \frac{\left| 0.06 + 0.06 + ... + 0.00 \right|}{15}$$

$$= 0.04$$

Standard deviation (quadratic), Stdq =

$$Std_q = \sqrt{\frac{\sum_{i=1}^{15}(each\ \ trial\ \ of\ \ linear\ \ quadratic\ - average\ \ of\ \ quadratic\ \ error)}{\sum No.of\ \ trial\ (T)-1}} \quad \textbf{(13)}$$

= 0.028

5. Conclusions

This research work was undertaken to develop a mathematical relationship between the tool life in end milling of hard material (AISI D2) and the machining variables by using the experimental results obtained through use of the concept of RSM. It has been possible to develop the first order (linear model) as well as the second order (quadratic model). Adequacy or validity of the models has been evaluated by ANOVA which indicates that the models are reliable. These models can be safely used to predict the tool life of the machined part of AISI D2 tool steel under the specified cutting conditions. These models are valid within the ranges of the cutting parameters in end milling which for cutting speed range is 40 - 80 m/min, for depth of cut range is 0.5 - 2.0 mm and for feed range is 0.05 - 0.1 mm/tooth. Both models linear (1^{st} order) and CCD quadratic (2^{nd} order) have shown similar trends indicating that the cutting speed has the most significant influence on tool life followed by feed and depth of cut. Hence, the percentage average of error between the predicted and measured tool life of both models is less than 10% but for quadratic model we found the average percentage error is less than 5%. Finally, a reliable technique for modelling tool life knowledge in end milling operations has been demonstrated in this paper.

Acknowledgement

This study was conducted under the purview of the e-science project (03-01-08-SF0003) entitled "Enhancement of Machinability of Hardened Steel in End Milling Using Advanced Cutting Methods and Tools", funded by the Ministry of Science, Technology and Innovation of Malaysia (MOSTI). The authors gratefully acknowledge the financial support.

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