Jurnal Mekanikal
June 2006, No. 21, 65-71

THE RELIABILITY OF TOOL LIFE PREDICTION MODEL IN END MILLING

[1]Jaharah A. Ghani
[2]Firdaus Mohamad Hamzah
[1]Mohd. Nizam Ab. Rahman
[1]Baba Md. Deros

[1]Department of Mechanical and Material Engineering
Faculty of Engineering

[2]Unit Pengajian Asas
Faculty of Engineering
Universiti Kebangsaan Malaysia
43600 UKM, Bangi, Selangor, Malaysia.

ABSTRACT

This paper describes the tool life prediction model when end milling AISI H13 tool steel using P10 TiN coated carbide tool. The development of the model utilizes the data set from the Taguchi method design of experiment with $L_{18}(2^1x3^7)$ orthogonal array. The effects of cutting speed, feed rate and depth of cut on tool life of P10 are discussed. A prediction model for speed within the region of 224 m/min to 355 m/min, feed rate of 0.1 mm/tooth to 0.25 mm/tooth, and depth of cut of 0.3 mm to 0.8 mm are presented. The adequacy of the predicted model after performing multiple regression analysis give 95% confidence interval with coefficient of multiple determination (R^2) of 0.845. Whereas from average percentage deviation ($\bar{\phi}$) calculated, it shows that the accuracy of the predicted model is only 23%. This shows that the accuracy of the predicted model could not depend solely on the analysis performed using SPSS alone. Other methods to check the model accuracy such as average percentage deviation ($\bar{\phi}$) are also important.

Keywords: *Tool life model, coated carbide tool, AISI H13 tool steel, SPSS, average percentage deviation ($\bar{\phi}$)*

1.0 INTRODUCTION

The criterion for the end of tool life is varied, either the tool is reground or replaced when it fails to cut and ceases out, when the dimensions or surface finish of the work-piece change, or when the temperature begins to rise and fumes are generated [1]. The symptoms of the end of tool life should be detected to avoid damage caused by total tool failure. Wear of cutting edge, which is caused mainly by load, friction, and high temperature, is the crucial factor in determining the tool life.

A lot of data has been practically collected in order to establish an adequate functional relationship between the tool life and cutting parameters of cutting speed, feed rate, and depth of cut. This problem arises due to the requirement of a separate set of tests for each cutting parameters combination for a specific cutting tool and work-piece material. The total number of tests increases as a full factorial is used, and consequently increases the cost of experimentation and is extremely time consuming. The fractional factorial design of experiment introduced by Taguchi [2] significantly reduces the number of experiments. Another fractional factorial to build tool life prediction model is a response surface method as described by Choudhury and Baradie [3]. Applications of regression are numerous and occur in almost every field, including engineering, physical sciences, and etc. Regression analysis is a statistical technique for investigating and modelling the relationship between variables [4], with the main objective to estimate the unknown parameters in the regression model. Parameter estimation technique used here is the method of least squares. Later the model adequacy is checked to study the appropriateness of the model by determining the coefficient of multiple determination (R^2). The regression model accuracy could also be checked using average percentage deviation ($\bar{\phi}$) as given by Lou et al. [5].

$$\phi_i = \frac{\left| Ti - \hat{Ti} \right|}{Ti} \times 100 \tag{1}$$

where ϕ_i: percentage deviation of single sample data

Ti: actual tool life time measured

$\hat{Ti}$: predicted tool life from multiple regression equation

$$\bar{\phi} = \frac{\sum_{i=1}^{m} \phi_i}{m} \tag{2}$$

where $\bar{\phi}$: average percentage deviation of all sample data

m: the sample size data

The study was carried out by simultaneously varying the cutting parameters of cutting speed, feed rate, and depth of cut and fitting the values in a standard orthogonal array design by Taguchi [2]. For the purpose of the model building, regression analysis was performed with the aid of SPSS software. The accuracy of the model building is checked by finding the coefficient of multiple determination (R^2) and average percentage deviation of all sample data ($\bar{\phi}$).

1.1 Tool Life Model

The relationship between the independent variables of milling parameters (cutting speed, feed rate and depth of cut) and machining response of tool life can be represented by the following mathematical model :

$$T = C(v^l f^m d^n)\varepsilon' \qquad (3)$$

where T is tool life in minutes, v, f, and d are the cutting speed (m/min), feed rate (mm/tooth) and depth of cut (mm) respectively. C, l, m, n are constants and ε is a random error. Equation 3 can be written in the following logarithmic form :

$$\ln \mathrm{T} = \ln \mathrm{C} + \mathrm{l} \ln \mathrm{V} + \mathrm{m} \ln \mathrm{f} + \mathrm{n} \ln \mathrm{d} + \ln \acute{\varepsilon} \qquad (4)$$

In SPSS, equation (4) that predicts the tool life can be rewritten in the following form:

$$T_{P10}(\text{predicted tool life}) = \text{constant} + \beta_1 v + \beta_2 f + \beta_3 d \qquad (5)$$

Instead of just an intercept and slope, the multiple linear regression equation contains a constant (analogous to intercept) and three coefficients $(\beta_1$-$\beta_3)$, one for each of the three independent variables [6]. These coefficients are called partial regression coefficients. Before using the SPSS, one needs to assume that the relationship between the dependent and independent variables is linear and that for each combination of values of the independent variables, the distribution of the dependent variable is normal with a constant variance. If the independent variables are not linearly related to the dependent variable, in order to estimate the coefficients, one has to transform the data as explained by Norusis [6]. The linear relationship of the dependent and independent variables can be graphically visualized with the scatter plot matrix available in the SPSS software.

2.0 EXPERIMENTAL DESIGN AND MILLING PARAMETERS

In order to develop the prediction model using Taguchi design of experiment, three factors at three levels each, the fractional factorial design of L_{18} orthogonal array was used [1]. Each row of the matrix represented one trial. However, the sequence in which those trials were carried out was random. The three levels of each factor were represented by a '0' or a '1' or a '2' in the matrix. The factors and levels were assigned as in Table 1 according to semi-finishing and finishing conditions for the material when machining at high cutting speed.

The factors A, B, and C were arranged in columns 2, 3, and 4 in L_{18} $(2^1 \text{ x} 3^7)$ orthogonal array.

The machining trials were carried out on a Cincinnati Milacron Sabre 750 Vertical Machining Centre in dry condition, as recommended by the tool supplier for AISI H13 tool steel (HRC50±3). The cutting tool used was flat end mill P10 TiN coated carbide. During the milling operation the insert was periodically removed from the tool holder, and flank wear and surface finish were measured accordingly. The length of each cutting path was 0.103 m. The tool wear on the flank face was measured after the first path. The wear measurement requirement would then depend on the rate of the wear growth. The measured parameter to represent the progress of wear was maximum tool wear VB_{max}.

Table 1: Factors and levels used in the experiment

Factor / Level	0	1	2
A – speed (m/min)	224	280	355
B – feed (mm/tooth)	0.1	0.16	0.25
C – radial depth of cut (mm)	0.3	0.5	0.8
Axial depth of cut was kept constant at 3 mm.			

3.0 RESULTS AND PREDICTION MODEL

Table 2 shows the results obtained with L_{18} $(2^1 \times 3^7)$ orthogonal array for tool life when the flank wear land (VB) was limited to 0.2 mm along with the experimental conditions.

Table 2: Experimental conditions and results

Experiment number/ Factors	A	B	C	Designation	Tool life (min)
1	0	0	0	A0B0C0	12.6
2	0	1	1	A0B1C1	5.6
3	0	2	2	A0B2C2	1.6
4	1	0	0	A1B0C0	28.9
5	1	1	1	AIBICI	2.5
6	1	2	2	A1B2C2	0.3
7	2	0	1	A2B0C1	11.7
8	2	1	2	A2B1C2	1.7
9	2	2	0	A2B2C0	7.2
10	0	0	2	A0B0C2	3.6
11	0	1	0	A0B1C0	20.1
12	0	2	1	A0B2C1	2.5
13	1	0	1	A1B0C1	11.6
14	1	1	2	A1B1C2	1.4
15	1	2	0	A1B2C0	19.3
16	2	0	2	A2B0C2	4.0
17	2	1	0	A2B1C0	13.4
18	2	2	1	A2B2C1	3.6

After transforming the data to get the linear relationship between the dependent and independent variables for tool life data, the following tool life prediction model is produced based on 18 trials using SPSS:

$$\ln T_{P10}(\,predicted\ tool\ life\,) = -2.359 - 1.279 \ln f - 2.30 \ln d \qquad (6)$$

The model describes the data adequately at 95% confidence interval as shown in Table 3 with coefficient of multiple determination (R^2) of 0.845.

Table 3: ANOVA for tool life model of P10 L_{18} (2^1x3^7) experiment using stepwise method for F-test at 95% confidence interval

Model	Sum of squares	df	Mean square	F	Sig.
Regression	404.198	4	101.049	27.826	.000
Residual	32.683	9	3.631		
Total	436.881	13			

Evaluating model adequacy is an important part of multiple regression problems. Besides the coefficient of multiple determination (R^2), the average percentage deviation ($\bar{\phi}$) [5] calculated from the multiple regression models plays an important role in judging model adequacy. The average percentage deviation ($\bar{\phi}$) calculated is equal to 77% from the data set of 18 trials. This shows that the predicted model could only predict the tool life (T) with about 23% accuracy. Therefore the coefficient of multiple determination (R^2) alone is not sufficient to check the accuracy of regression model.

Equation (6) indicates that the tool life is dependent of the depth of cut and feed rate with the effect of depth of cut being higher in determining the tool life. The reason why such a model was developed is based on the following discussion from previous researchers. The cutting edge temperature increases with the increase in depth of cut [7] and feed rate strongly influences the range of chip thickness from tooth entry to exit [8], and chip area on the end mill [9]. Both of these values determine the amount of cutting force during machining operation. Increasing the feed rate and depth of cut values results in higher cutting force, which requires more power consumption to remove the material and consequently generates more heat at the tool edge, promoting tool wear and shortening the tool life. From the regression analysis the equation reveals that the cutting speed is not significant, which is contrary to earlier claims by several researchers [10-12] who found that tool life decreases drastically as cutting speed is increased. The fact is that at high cutting speed high temperature will be generated which accelerates tool wear and consequently shortens the tool life. Therefore, it can be concluded that in this range of feed rate and depth of cut, the effect of cutting speed is less significant. However, above or below this range, there is a possibility that the effect of cutting speed is significant. In addition, the mode of tool failure is another important factor in determining the tool life. When high feed and depth of cut values are used, high impact force experienced on the cutting edge would initiate cracks on the coating material. This is probably due to the brittle TiN ceramic coating material which serves as a region of easy crack initiation, and therefore increases the tendency towards fracture [13]. Increasing or decreasing cutting speed would not initiate the crack on the TiN material. This is found to be the main reason why cutting speed has no effect on the tool life, since most of the tools failed due to crack and fracture of the cutting edge.

4.0 CONCLUSIONS

1. The tool life equation shows that the depth of cut is the main factor affecting the tool life, followed by the feed rate. On the other hand, cutting speed effect is less significant within the testing region of cutting speed, feed rate and depth of cut.
2. The effect of cutting speed is less significant since the tool failure is due to higher cutting force generated by a combination of high feed rate and depth of cut.
3. The predictive model developed is adequate at 95% confidence limit with the coefficient of multiple determination (R^2) of 0.845 by regression analysis using SPSS. But the average percentage deviation ($\bar{\phi}$) calculated is equal to 77%, which means that the predicted model could only predict the tool life (T) with about 23% accuracy.
4. The coefficient of multiple determination (R^2) alone is found to be insufficient to check the accuracy of regression model. The average percentage deviation ($\bar{\phi}$) is an important factor when considering the accuracy of such a model.

REFERENCES

1. Trent E.M., 1991, *Metal Cutting*, 3rd. Edition, Butterworth Heinemann, London.
2. Park S.H.,1996, *Robust Design and Analysis for Quality Engineering*, Chapman and Hall.
3. Choudhury I.A., and El-Baradie M.A., 1998, Tool life prediction model by design of experiments for turning high strength steel (290 BHN), *Journal of Material Processing Technology*, 77, pp. 319-326
4. Montgomery D.C., and Peck E.A., 1982, *Introduction to linear regression analysis*, John Wiley & Sons.
5. Cole S.M., Chen C.J, and Li C.M.,1995, Surface roughness prediction technique for CNC end milling, *Journal of Industrial Technology*, Vol. 15, No.1, pp. 1-6
6. Norusis M.J., 1995, SPSS 6.1, *Guide to data analysis*, Prentice Hall.

7. El-Wardany, Mohammed E., and Elbestawi M.A., 1996, Cutting temperature of ceramic tools in high speed machining of difficult-to-cut-materials, *International Journal of Machine Tools*, Vol 36, No 5, pp. 611-634.
8. Melkote S.N. and Endres W.J., 1998, The importance of including size effect when modeling slot milling, *Transactions of ASME*, Vol. 120, pp. 68-75.
9. Sutherland J.W., and Devor R.E., 1986, An improved method for cutting force and surface error prediction in flexible end milling systems, *Journal of Engineering for Industry*, 86, Vol. 108, pp. 269-279.
10. Urbanski J.P., Koshy P., Dewes R.C., and Aspinwall D.K., 2000, High speed machining of mould and dies for net shape manufacture, *Materials and Design* 21, pp.395-402.
11. Abrao A. M., Wise M.L.H., and Aspinwall D.K., 1995, *Tool life and workpiece surface integrity evaluations when machining hardened AISI H13 and AISI E52100 steels with conventional ceramic and PCBN tool materials,* Technical Paper, MR 95-159, Society of Manufacturing Engineers.
12. Komanduri R., Flom D.G., and Lee M., 1985, Highlights of the DARPA Advanced Machining Research Program, *Journal of Engineering for Industry*, Vol. 107, pp. 325-335.
13. Kramer B.M., 1987, On tool materials for high speed machining, *Journal of Engineering for Industry*, Vol. 109, pp. 87-91.