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TOOL LIFE ANALYSIS BY PARTIAL SWARM OPTIMISATION

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ABSTRACT

Tool life is one of the main factors to be considered in CNC milling machine. Prediction model and optimum values are very important for the machinist to save number of cutting tools and reduce machining time. The aim of the this paper is to develop the tool life prediction model for P20 tool steel with aid of statistical method and to determine the optimisation values using partial swarm optimisation (PSO) for coated carbide cutting tool under different cutting conditions. By using response surface method, first and second order models were developed with 95% confidence level. The tool life model was developed in terms of cutting speed, feed rate, axial depth and radial depth. In general, the results obtained from the mathematical model are in good agreement with that obtained from the experiment data's. It was found that the feed rate, cutting speed, axial depth and radial depth played a major role to determine the tool life. On the other hand, the tool life increases with the reduction of cutting speed and feed rate. For end-milling of P20 tool steel, the optimum cutting speed, feed rate, axial depth and radial depth obtained from PSO are of 100 m/s, 0.1 mm/rev, 1.9596 mm and 2 mm respectively. The optimized tool life of 40.52 min was obtained using the above mentioned parameters.

Keywords: End-milling, Tool life, response surface method, partial swarm optimisation, cutting speed, feed rate, depth of cut.

INTRODUCTION

The tool life is an important for metal cutting since considerable time, which is lost whenever a tool is replaced or re-set. The cutting tool looses it's sharpness as usage continues and their effectiveness decrease over time. At some point during the life-span of the tool, it is necessary to replace, index or re-sharpen and reset the tool. The life of cutting tool depends upon many factors including the microstructure of the material being cut, metal removal rate, rigidity of the setup and effects of cutting fluid (David and John, 1997; Krar, 1995). The proper choice of cutting velocity can enhance the tool life, however, the tool should be used to its maximum capacity at the same time. Sharman *et al.* (2001) were studied that the tool coating was found to be the main factor affecting the tool life followed by cutting speed and workpiece angle. According to Alauddin *et al*. (1997), an increase of the cutting speed, feed rate and axial depth of cut would decrease the tool life. Response surface method (RSM) saves the cost and time on conducting the metal cutting experiments by reducing the overall number of required tests. In addition, RSM helps the describe and identify, with a great accuracy, the effect of the interactions of different independent variables on the response when they are varied simultaneously (Mead and

Pike, 1975; Hill and Hunter, 1966; and Hicks, 1993). RSM has been extensively used in the prediction of responses such tool life, surface roughness and cutting forces. Up-to-date, few researches were used RSM to study the effect of cutting conditions on the tool life when end-milling of tool steel used to produce plastic injection moulds such as modified AISI P20 steel.

Childs *et al.* (2000) and Trent and Wright (2000) suggested that tool life is directly related to the wear behaviour of the cutting tool. The workpiece material and its physical properties (the mechanical and thermal properties, microstructure hardness etc) determine the cutting forces and energy for the applied cutting conditions. According to Devillez *et al.* (2004) and O'Sullivan and Cotterell (2001), crater wear is a temperature dependent process, dissolution and diffusion mechanisms. Tool wear results in undesirable effects such as loss in dimension accuracy of finished product, possible damage to the workpiece, decreased surface integrity, residual strain, roughness and amplification of chatter during the cutting process reported by some researchers (Wang *et al*., 2003), (Chou and Evans, 1997) and (Choudhury and Kishore, 2000). Due to the complexity and unpredictable nature of the machine process, the process has to be modelled with rule-based techniques. In this paper, Partial Swarm Optimisation model is to be proposed to obtain the optimum tool life and RSM is used to reduce the number of experiments.

RSM MODELS FOR TOOL LIFE

The proposed linear model relationship between the machining responses and independent variables can be expressed as in Eq. (1):

$$y = m \times \text{Cutting speed} + n \times \text{Feed rate} + p \times \text{Axial depth} + q \times \text{Radial depth} + C \tag{1}$$

where y is the response, C, m, n, p and q are the constants. Equation (1) can also be expressed as Eq. (2):

$$y = \beta_0 x_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 \tag{2}$$

where y is the response, x_0 = 1(dummy variables), x_1= cutting speed, x_2 = feed rate, x_3= axial depth and x_4 = radial depth. β_0 = C and β_1, β_2, β_3, and β_4 are the model parameters. In most cases, the response surface variables demonstrate some curvature in most ranges of the cutting parameters. Therefore, it would be useful to consider the second order model in this study. The second order model assists the effect of second order factor separately and the two-way interaction amongst these factors combined. This model can be represented by Eq. (3):

$$\begin{aligned} y'' = {} & \beta 0xo + \beta 1x1 + \beta 2x2 + \beta 3x3 + \beta 4x4 + \beta 11x_1^2 \beta 22x_2^2 + \beta 33x_3^2 \\ & + \beta 44x_4^2 + \beta 11x1x2 + \beta 12x1x3 + \beta 13x1x4 + \beta 14x2x3 + \beta 15x3x4 \end{aligned} \tag{3}$$

PARTIAL SWARM OPTIMISATION

Partial swarm optimisation algorithm is similar to that of the evolutionary computation techniques in which a population of potential solutions to the optimal problem that is used to probe the search space. Each potential solution is assigned a randomized velocity and the potential solution, which is called *particles*, correspond to individuals. Each particle in PSO flies in the D-dimensional problem space with velocity dynamically adjusted according to the flying experiences of its individuals and their colleagues. The location of the ith particle is represented as $X_i=[x_{i1}, x_{i2},\ldots \ldots \ldots, x_{id}]$, where $x_{id} \in [I_d,u_d]$, $d \in [1,D]$, I_d,u are the lower and upper bounds for the d^{th} dimension respectively. The best previous position (which gives the best fitness value) of the i^{th} particle is recorded and represented as $P_i=[p_{i1}, p_{i2},\ldots, p_{iD}]$, which is also called P_{best} . The index of the best particle among all the particles in the population is represented by the symbol, g. The location P_g is denoted by g_{best} . The velocity of the i_{th} particle is represented by $V_i=[v_{i1}, v_{i2},\ldots, v_{iD}]$ and is clamped to a maximum velocity $V_{max}=[v_{max1}, v_{max2},\ldots, v_{maxD}]$, which is specified by the user. The particle swarm optimization concept consists of, at each time step, regulating the velocity and location of each particle toward its P_{best} and g_{best} locations according to the Eq. (4) and Eq. (5) respectively (Liu and Xiongxiong, 2005).

$$v_{id}^{n+1} = w v_{id}^{n} + c_1 r_1^{n} (p_{id}^{n} - x_{id}^{n}) + c_2 r_2^{n} (p_{gd}^{n} - x_{id}^{n}) \tag{4}$$

$$x_{id}^{n+1} = x_{id}^{n} + v_{id}^{n+1} \tag{5}$$

The PSO outputs have been termed as one output node representing the state variable (tool life) as shown in Fig. 1. The experimental results are used for the optimisation of the tool life model using the PSO. The codes for PSO are written by MATLAB coding which follows the logic of the pseudocode as shown in Fig. 2.

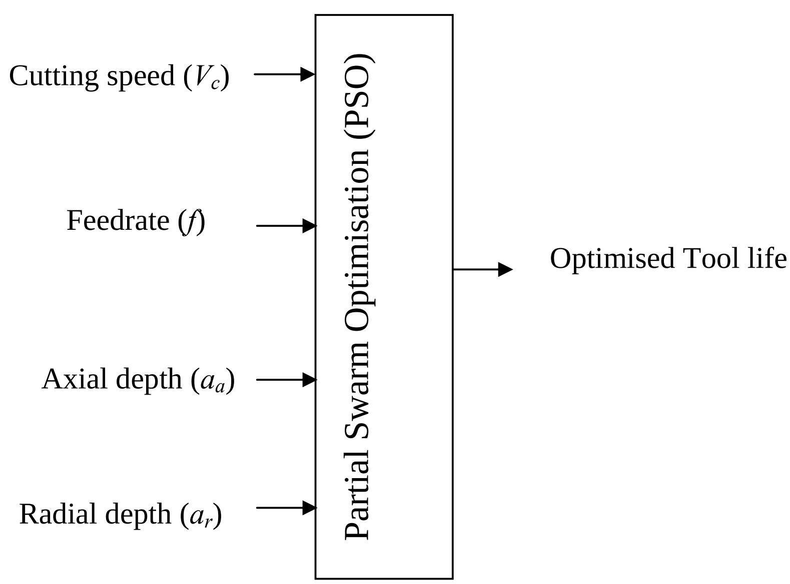

Figure 1: PSO for paddle cantilever

```
For each particle
   Initialize particle
END

Do
   For each particle
      Calculate fitness value
      If the fitness value is better
than the best fitness value (pBest)
in history
         set current value as the new
pBest
   End
   Choose the particle with the best
fitness value of all the particles as
the gBest
   For each particle
      Calculate particle velocity
according equation (a)
      Update particle position
according equation (b)
   End
```

Figure 2: A pseudo-code for PSO

EXPERIMENTAL PROCEDURE

The parameters β_0, β_1, β_2, etc, appearing in Eq. 2, are determined using the method of least squares. The calculations are performed using Minitab. In order to reduce the total number of cutting tests and allow simultaneous variation of the four independent factors, a well-designed experimental procedure has to be followed. In machining research, the Box-Behnken design has found a broad application compared to other experiment designs used for RSM. The Box-Behnken design is based on the combination of the factorial with incomplete block designs. It does not require a large number of tests as it considers only three levels (-1, 0, 1) of each independent parameter (Box and Behnken, 1960). The levels of the four input independent variables are given in Table 1. The Box-Behnken design is normally used for non-sequential experimentation, when a test is conducted only once. It allows an efficient evaluation of the parameters in the first and second order models. Using Minitab the cutting conditions of 29 experiments are generated and the experiments are conducted randomly to minimise errors. In order to calculate the experimental error, the 29 experiments consider five times repeating of central point of the cutting conditions. After a series of preliminary trial tests had been conducted and based on the recommendations given by the tool and workpiece manufacturers, the cutting conditions of the main experiments were established in Table 2.

Table 1 Levels of independent variables

Factors \ Coding of Levels	-1	0	1
Speed, V_c (m/s)	100	140	180
Feed, f (mm/rev)	0.1	0.2	0.3
Axial depth of cut, a_a, (mm)	1	1.5	2
Radial depth of cut, a_r, (mm)	2	3.5	5

The current study is concerned with investigating the effect of four factors (cutting speed, feed, axial depth of cut and radial depth of cut) on the tool life when end milling of modified AISI P20 tool steel with coated carbide inserts. Generally, AISI P20 is a chromium-molybdenum alloyed steel which is considered as a high speed steel used to build moulds for plastic injection and zinc die-casting, extrusion dies, blow moulds, forming tools and other structural components. The modified form of AISI P20 is distinguished from normal P20 steel by the balanced sulphur content (0.015 %) which gives the steel better machinability and more uniform hardness in all dimensions. Modified AISI P20 possesses a tensile strength of 1044 MPa at room temperature and a hardness ranging from 280 to 320 HB. The workpiece used in this study was pre-hardened and tempered to a minimum hardness of 300 HB and was provided by ASSAB (Sweden). The approximate chemical analysis is shown in Table 3.

Table 2 Conditions of cutting experiments according to Box-Behnken design

Experiment Number	Cutting speed, V_c (m/min)	Feed, f (mm/rev)	Axial depth of cut, a_a (mm)	Radial depth of cut, a_r (mm)
1	140	0.15	1.0	2.0
2	140	0.20	1.0	3.5
3	100	0.15	1.0	3.5
4	180	0.15	1.0	3.5
5	140	0.10	1.0	3.5
6	140	0.15	1.0	5.0
7	100	0.15	1.5	2.0
8	140	0.10	1.5	2.0
9	100	0.20	1.5	3.5
10	140	0.15	1.5	3.5
11	180	0.20	1.5	3.5
12	180	0.15	1.5	2.0
13	140	0.20	1.5	2.0
14	140	0.20	1.5	5.0
15	140	0.15	1.5	3.5
16	180	0.10	1.5	3.5
17	100	0.10	1.5	3.5
18	100	0.15	1.5	5.0
19	140	0.10	1.5	5.0
20	180	0.15	1.5	5.0
21	140	0.15	1.5	3.5
22	140	0.15	2.0	5.0
23	140	0.20	2.0	3.5
24	140	0.10	2.0	3.5
25	140	0.15	2.0	2.0
26	100	0.15	2.0	3.5
27	180	0.15	2.0	3.5
28	140	0.15	1.5	3.5
29	140	0.15	1.5	3.5

Table 3 Chemical analysis of modified AISI P20, %

Chemical Composition	Weight (%)
C	0.38
Si	0.30
Mn	1.50
Cr	1.90
Mo	0.15
S	0.015
Fe	bal

The cutting tool used in this study is a 0º lead – positive end milling cutter of 31.75–mm diameter. The end mill can be equipped with two square inserts whose all four edges can be used for cutting. The tool inserts were made by Kennametal and had an ISO catalogue number of SPCB120308 (KC735M). In this study, only one inserts per one experiment was mounted on the cutter. The insert had a square shape, back rake angle of 0º, clearance angle of 11º, and nose radius of 0.794 mm and had chip breaker. KC735M inserts are coated with a single layer of TiN. The coating is accomplished using PVD techniques to a maximum of 0.004–mm thickness.

The 29 experiments were performed in a random manner on Okuma CNC machining centre MX-45 VA and using a standard coolant. Each experiment was stopped after 85 mm–cutting length. Each experiment was repeated three times using a new cutting edge every time to obtain very accurate readings of the tool life. A cutting pass was conducted in such a way that a shoulder, of depth ranging from 1 to 2 mm, and width of 2 to 5 mm, was produced. From the microscope, the flank wear was measured as shown in Figure 3. Firstly draw the horizontal line as the reference line, then draw the vertical line from the reference line to measure the flank wear. Figure 4 shows the experimental setup employed in this study.

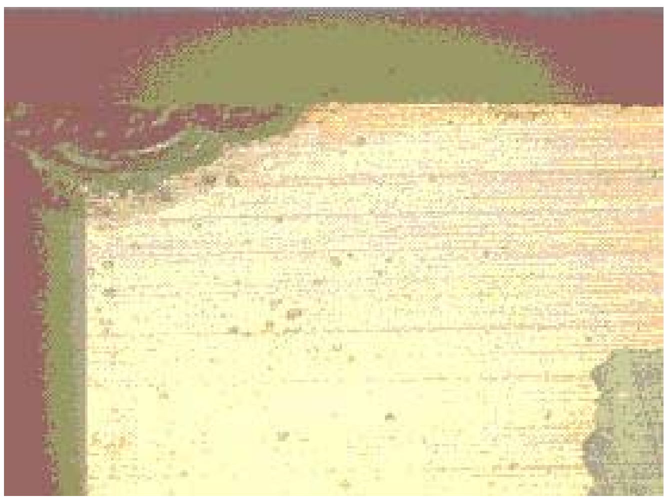

Figure 3 Measurement of flank wear

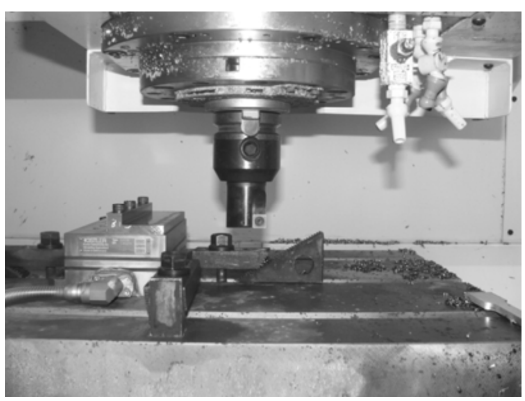

Figure 4 Experimental Setup

RESULTS AND DISCUSSION

Development of First and second Order Tool life Model

Tool life can be expressed as in Eq. (6). (Krar, 1995):

$$y = \frac{Fm}{TL} \tag{6}$$

where *Fm* is feed in mm/min and *TL* is total length.

The first order linear model for predicting the tool life by RSM is expressed as in Eq. (7):

$$y = 47.76 - 0.12\, x_1 - 141.03\, x_2 + 4.43\, x_3 - 1.83\, x_4 \tag{7}$$

Equation (7) shows that the tool life decreases with increases of the cutting speed, the feed rate, radial depth and axial depth. The feed rate has the most dominant effect on the tool life, followed by the cutting speed, axial depth and radial depth. Hence, a better tool life is obtained with the combination of less cutting speed and low feed. According to Choudhury (1999), the effect of feed rate on tool life is much more pronounced than the effect of speed. Alauddin *et al.* (1997) found that an increase in the cutting speed, feed, and axial depth of cut decrease the tool life. According to Trent (1991), due to the high normal stress exerted on the tool rake face during cutting, a seizure (or sticking) zone occurs at the chip–tool interface, where the chip velocity is zero and the actual contact area is equal to the apparent area. Because the chip velocity is zero in this region, a large amount of shearing happens inside the chip located just above this interface. Therefore, heat generation is very high in this region. On the other hand, lubrication is difficult owing to the complete contact between the tool and the chip. Figure 5 shows the tool life obtained by experiment and predicted by the first order model. The two-dimensional microscopic wear image at high, medium, low tool life conditions are also shown in Figure 5. It is clear that the predicted values are very close to the experimental results. The cutting tool with high tool life demonstrate low flank wear meanwhile for tool life range 2~5 min the tools damage with high wear as shown in Figure 5.

The adequacy of the first order model was verified using the analysis of variance (ANOVA). At a level of confidence of 95%, the model was checked for its adequacy. As it is shown in Table 4, indicates that the model is adequate since the p-values of the lack-of-fit are not significant and F-ratio is 3.58. This implies that the model could fit and it is adequate.

The second-order model was developed to obtain the interaction between the variables. The second order model can be expressed as in Eq. (8):

$$\begin{aligned} y'' = {} & 18.79 + 0.66 x_1 - 924.84 x_2 + 41.24 x_3 - 1.75 x_4 - 0.0011 x_1^2 \\ & + 2282.9\, x_2^2 - 5.40 x_3^2 + 1.38 x_4^2 - 1.13 x_1\, x_2 - 0.05 x_1\, x_3 \\ & - 0.068 x_1\, x_4 - 43.9\, x_2\, x_3 + 61.4\, x_2\, x_4 - 5.73 x_3\, x_4 \end{aligned} \tag{8}$$

Table 5 shows that 95% of confidence interval for the experiments and analysis of variance. For the second-order model, the p-value for lack of fit is 0.109, which is not significant. Therefore, the model is adequate. The variables are not significantly interact among them since the p-value is 0.788 (> 0.05).

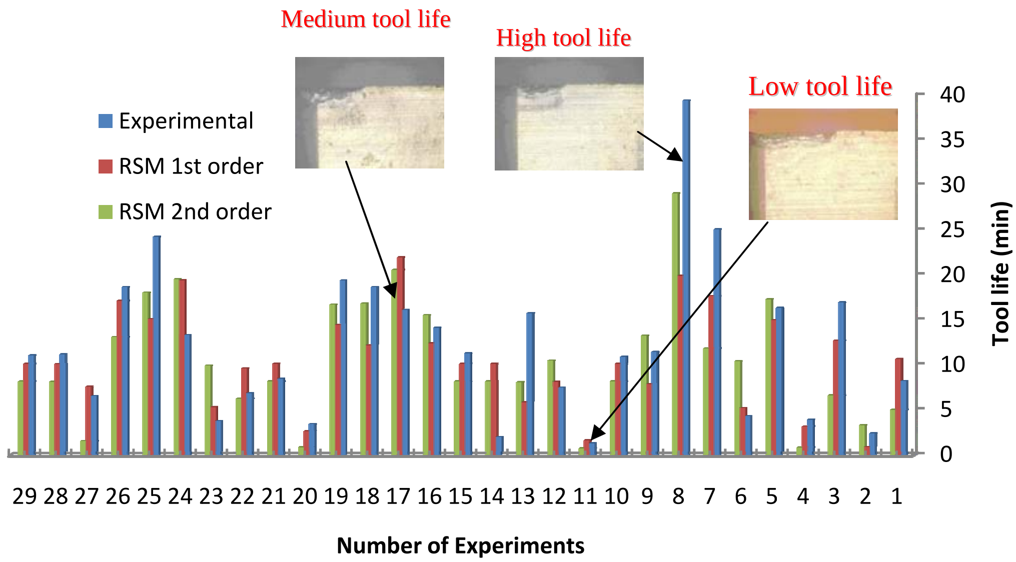

Figure 5 Comparison between experimental and prediction results for first order model.

Table 4. Variance analysis (ANOVA) for first order tool life model.

Source	DF	F-ratio	p-value
Regression	4	3.85	0.016
Linear	4	3.85	0.016
Residual Error	22		
Lack-of-Fit	19	3.58	0.160
Pure Error	3		
Total	26		

Table 5. Variance analysis for second order tool life model.

Source	DF	F-ratio	p-value
Regression	14	1.34	0.308
Linear	4	2.36	0.112
Square	4	0.91	0.488
Interaction	6	0.51	0.788
Residual Error	12		
Lack-of-Fit	9	4.89	0.109
Pure Error	3		
Total	26		

Validation with Experimental Results

The optimised tool life model is tested with the experimental results. Comparison between the optimized predicted results obtained from the PSO model and the experimental results are given in Table 6. The validation experiment is performed in the same machining environment as the training experiment. The error of tool life obtained by optimised tool life model is 5.46%.

Table 6 Comparison between optimisation and experimental results

Parameters	Value	Unit
Cutting Speed	100	(m/mim)
Feed rate	0.1	(mm/rev)
Axial depth	2	(mm)
Radial depth	2	(mm)
Experimental tool life	38.42	(min)
Predicted tool life	40.52	(min)
Deviation	5.46	%

CONCLUSION

This research illustrates the machining of P20 tool steels with end-milling methods and predicting their subsequent tool life. There is becoming a need for investigating the machining of various types of tool steels and their tool life which in turn can be useful in developing more cost effective personalised products. The authors have shown the use of PSO to formulate an optimised tool life prediction model for end machining of P20 tool steel. This prediction model is tested on the validation experimental and the error analysis of the prediction result with the measured results is estimated as 5.46 % which is small and shows the efficacy of the prediction model. Finally, the simulation results show that PSO combine with RSM can be very successively used for reduction of the effort and time required. This means that it can solve many problems that have mathematical and time difficulties. A first and second order Mathematic Model were developed to predict cutting parameters for end-milling of P20 tool steel using coated carbide tool steel. The model developed was used to calculate the tool life based on Response Surface Method (RSM). The results were compared by experimentation. In general, the results obtained from the mathematical model are in good agreement with that obtained from the experiment data’s. It was found that the feed rate, cutting speed, axial depth and radial depth played a major role in determining the tool life. On the other hand, the tool life increases with a reduction in cutting speed and feed rate. In addition, the second order model proves that there is no interaction among the variables.

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