Discrimination of the tool failure patterns with simultaneous approach of fuzzy clustering, principal components and multiple regression analysis

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Abstract

In cutting hardened die steel with carbide end mill, the criterion for judging a tool life are divided broadly into three categories, that is, progressive wear, chipping or breakage. Among them, the prediction of the tool life caused by the wear is relatively easy, but it is difficult to estimate the tool life caused by the remaining two. Thus it is desirable to select the cutting conditions which lead to a tool life caused by the wear. In this study Holm's value which has relation with an average cutting force and attrition length between work and tool is considered to be one of factors affecting tool failure pattern. In order to identify a mathematical model for predicting the tool failure patterns, simultaneous approach to fuzzy clustering, principal components and multiple regression analysis is applied. In the approach the initial and the maximum cutting force, the number of cutting, attrition length and Holm's value are chosen as predictor variables from the tool life tests using carbide end-mill, and the tool failure patterns (wear, chipping and breakage) as response variables. As the results, two clusters are obtained. The data in the 1st cluster indicates that small initial cutting force, long attrition length and many number of cutting have an effect on the tool life caused by wear. By contrast to the 1st it is shown from the 2nd cluster that large initial cutting force, short attrition length and small number of cutting affect on the tool life caused by breakage. According to the approach it is possible to predict the tool failure patterns and to select the cutting conditions leading to the tool life caused by wear.

1. Introduction

In recent years (Al, Ti)N-coated micro-grain carbide end mills have been developed [1]. They are capable of machining hardened steel up to a hardness of approximately HRC53, and have found increased use in die/mold making. In order to realize high accuracy and productivity, it is important to choose the most appropriate cutting conditions and tool paths on the basis of the study of the wear process of the end mill. In the choice of the cutting conditions it is required to predict the tool life of the end mill. The criterion for judging a tool life are divided broadly into three categories, that is, wear, chipping or breakage. The end mill has a characteristic that the tool life decreases due to chipping and rapid increase of wear when cutting are not selected properly. Therefore the prediction of the tool life caused by wear is relatively easy, but it is difficult to estimate the tool life caused by the remaining two. Thus it is desirable to select the cutting conditions which lead a tool life caused by the wear. In this study Holm's value [2] is considered to be one of factors affecting tool life cause. The value is defined as the amount of wear determined by the product of weight and attrition length. In end milling the weight can be regarded as an average cutting force, and the length as the product of interference length between work and tool, and the number of cutting. To identify a mathematical model for predicting the tool failure patterns, simultaneous approach to fuzzy cluster, principal components and multiple regression analysis is applied. In the approach the initial and the maximum cutting force, the number of cutting, attrition length and Holm's value are chosen as predictor variables from the tool life tests using carbide end-mill, and the tool failure patterns (wear, chipping and breakage) as response variables. According to the approach it is possible to predict the tool failure patterns and to select the cutting conditions leading to the tool life caused by wear. That contributes to the construction of a cutting condition database for the determination of appropriate cutting conditions.

2. Simultaneous Approach to Fuzzy Cluster, Principal Components and Multiple Regression Analysis

In the regression problem, one is given n samples with s predictor variables and t response variables which are denoted by $x_1, \cdots, x_s$ and $x_{s+1}, \cdots, x_{s+t}$ respectively. Since it is difficult to deal with high dimensional data directly, the predictor vectors are projected on a low dimensional space spanned by the principal component vectors. Relatively low dimensional regression hyper planes are determined from projected predictor variables. From the predictor variables, we define $z_{c1}, z_{c2}, \cdots, z_{cp}$ $(p < s)$ as follows:

$$\begin{aligned} z_{c1} &= l_{c11}(x_1 - v_{c1}) + \cdots + l_{c1s}(x_s - v_{cs}) \\ &\vdots \\ z_{cp} &= l_{cp1}(x_1 - v_{c1}) + \cdots + l_{cps}(x_s - v_{cs}) \end{aligned} \tag{1}$$

where $c = 1, \cdots, C$. v_{ci} denotes the center of the cluster c. $\boldsymbol{z}_c$ are applied to the multiple regression analysis

$$x_{s+i} = \gamma_{ci1} z_{c1} + \gamma_{ci2} z_{c2} + \cdots + \gamma_{cip} z_{cp} + e_{ci} \tag{2}$$

The purpose of the proposed method is to obtain z_{ci} so as to minimize the sum of residual variance. In other words, we determine the coefficients l_{cij} which maximize the correlation μ_{ci} between the response variables and linear combinations z_{ci} of predictor variables.

$$\mu_{ci} = (\boldsymbol{l}_c^T \boldsymbol{r}_{ci})(\boldsymbol{l}_c^T S_c \boldsymbol{l}_c)^{-1/2}(t_{cii})^{-1/2} \tag{3}$$

where

$$S_c = \{s_{cij}\} \tag{4}$$

$$s_{cij} = \sum_{k=1}^{n} u_{ck}(x_i(k) - v_{ci})(x_j(k) - v_{cj}) \tag{5}$$

$$r_{cij} = \sum_{k=1}^{n} u_{ck}(x_i(k) - v_{ci}) \times (x_{s+j}(k) - v_{c(s+j)}) \tag{6}$$

$$t_{cij} = \sum_{k=1}^{n} u_{ck}(x_{s+i}(k) - v_{c(s+i)}) \times (x_{s+j}(k) - v_{c(s+j)}) \tag{7}$$

Our objectives are to maximize the correlation represented by

$$\sum_{c=1}^{C}\sum_{i=1}^{t} \mu_{ci} m_{c0i} = \sum_{c=1}^{C} \boldsymbol{l}_c^T R_c \boldsymbol{m}_c \tag{8}$$

where

$$m_{ci} = (t_{ii})^{-1/2} m_{c0i} \tag{9}$$

$$R_c = \{r_{cij}\} \tag{10}$$

and to minimize the within-group sum-of-squared-errors

$$\sum_{c=1}^{C}\sum_{k=1}^{n} u_{ck}||\boldsymbol{x}(k) - \boldsymbol{v}_c||^2 \tag{11}$$

To fix the unique $\boldsymbol{l}$ and $\boldsymbol{m}$, we set the constraints

$$\boldsymbol{l}_c^T S_c \boldsymbol{l}_c = 1 \tag{12}$$

$$\boldsymbol{m}_c^T \boldsymbol{m}_c = 1 \tag{13}$$

which represent that $\boldsymbol{l}_c$ and $\boldsymbol{m}_c$ have unit variance. By the Fuzzy c-Means clustering convention, we have

$$\sum_{c=1}^{C} u_{cj} = 1 \tag{14}$$

$$j = 1, 2, \cdots, n, c = 1, 2, \cdots, C$$

These objectives and constraints can be represented by a Lagrangean function as

$$\begin{aligned} L \quad = \quad & \sum_{c=1}^{C}\Big[\alpha\Big\{\boldsymbol{l}_c^T R_c \boldsymbol{m}_c - \frac{1}{2}\lambda_c^l(\boldsymbol{l}_c^T S_c \boldsymbol{l}_c - 1) - \frac{1}{2}\lambda_c^m(\boldsymbol{m}_c^T \boldsymbol{m}_c - 1)\Big\} \\ & -(1-\alpha)\sum_{k=1}^{n} u_{ck}||\boldsymbol{x}(k) - \boldsymbol{v}_c||^2 - \beta\sum_{k=1}^{n} u_{ck}\log u_{ck}\Big] \\ & -\sum_{k=1}^{n}\gamma_k(\sum_{c=1}^{C} u_{ck} - 1) \end{aligned} \tag{15}$$

where α is a constant to define the tradeoff between the principal component analysis, the multiple regression analysis and within-group sum-of-squared-errors. u_{ck}, which takes the value from interval $[0, 1]$, is the membership of the sample data k in the cluster c. β in the entropy term is a weighting parameter to specify degree of fuzziness of fuzzy clusters. This maximizing entropy approach was introduced by Miyamoto and Mukaidono [3]. Since the appropriate values of α and β depend on a given data set, we determine them by trial and error. λ_c^l, λ_c^m and γ_k are the Lagrangean multipliers. The necessary condition for optimality of L for $i \in (1, 2, \cdots, s)$ is as follows:

$$\begin{aligned}\frac{\partial L}{\partial v_{ci}} &= -\alpha \sum_{k=s+1}^{s+m} l_{ci} m_{ck} \sum_{j=1}^{n} u_{cj}(x_{jk} - v_{ck}) \\ &\quad + \frac{1}{2}\lambda_c^l \sum_{k=s}^{s} l_{ci} l_{ck} \sum_{j=1}^{n} u_{cj}(x_{jk} - v_{ck}) + 2(1-\alpha)\sum_{j=1}^{n} u_{cj}(x_{ji} - v_{ci}) \\ &= 0 \end{aligned} \tag{16}$$

A solution to Eq.(16) is

$$v_{ci} = \frac{\sum_{k=1}^{n} u_{ck} x_{ik}}{\sum_{k=1}^{n} u_{ck}} \tag{17}$$

We can obtain Eq.(17) for $i \in (s+1, s+2, \cdots, s+t)$ in the same manner. From $\partial L / \partial \boldsymbol{l}_c = 0$ and $\partial L / \partial \boldsymbol{m}_c = 0$, we have

$$S_c^{-1} R_c R_c^T \boldsymbol{l}_c = (\lambda_c)^2 \boldsymbol{l}_c \tag{18}$$

Accordingly, if R_c and S_c are non-singular matrices, z_c is obtained from the eigenvector $\boldsymbol{l}_c$ corresponding to the maximum eigenvalue λ_{max}^2 of the eigenvalue problem (18).

$$\lambda_c^l = \lambda_c^m = \boldsymbol{l}_c^T R_c \boldsymbol{m}_c \tag{19}$$

and

$$z_{c1} = \boldsymbol{l}_{c1}^T (\boldsymbol{x} - \boldsymbol{v}_c) \tag{20}$$

where

$$\boldsymbol{l}_{c1} = \frac{\boldsymbol{l}_c}{\sqrt{\boldsymbol{l}_c^T S_c \boldsymbol{l}_c}} \tag{21}$$

In the same manner, we can obtain $z_{c2} \sim z_{cp}$ from the eigenvectors corresponding to the second $\sim$ pth eigenvalues. From $\partial L / \partial u_{ck} = 0$, the memberships to clusters are obtained as follows:

$$u_{ck} = \frac{\exp(A_{ck})}{\sum_{m=1}^{C} \exp(A_{ak})} \tag{22}$$

$$\begin{aligned} A_{ak} &= \frac{\alpha}{\beta}\{\sum_{i=1}^{s}\sum_{j=1}^{t}(x_i(k) - v_{ai}) \times (x_{s+j}(k) - v_{a(s+j)}) l_{ai} m_{aj} \\ &\quad -\lambda_a \sum_{i=1}^{s}\sum_{j=1}^{s}(x_i(k) - v_{ai}) \times (x_j(k) - v_{aj}) l_{ai} l_{aj} \\ &\quad -\frac{1-\alpha}{\beta}\sum_{i=1}^{s+t}(x_i(k) - v_{ai})^2 \end{aligned} \tag{23}$$

The algorithm is as follows:

Step1 Randomly choose membership u_{ck}, $c = 1, \cdots, C$, $k = 1, \cdots, n$ from unit interval [0,1] and compute the cluster center vector $\boldsymbol{v}_c$ by Eq.(17)

Step2 Compute z_i, $i = 1, \cdots, p$ by using eigenvalues from Eq.(18).

Step3 Update $\boldsymbol{v}_c$ and u_{ck} by Eq.(17) and Eq.(22).

Step4 If $\max_{c,k} |u_{ck}^{NEW} - u_{ck}^{OLD}| < \epsilon$ then stop. Otherwise, go to Step2.

3. Experimental Conditions and Results

3.1 Tool and Work Piece

An (Al, Ti)N-coated micro-grain carbide radius end mill with a diameter of 10mm, a 45° helix angle and 6 flutes has been used in the experiments. The bottom corner of each cutting edge is rounded with a 1mm radius. The end mill has a wide core with a negative rake angle (-14°). The hardened steel JIS SKD61 with a hardness of HRC53 is chosen as the work piece material.

3.2 Experimental Equipment and Procedures

Work piece 1(SKD61) and Work piece 2(SKD61) are set on the table of a vertical type machining center as shown in Fig.1. Work piece 2 is mounted on the 3-axis dynamometer used to measure the cutting forces. The tool life tests[4] are performed by straight cutting (+Y direction) with constant axial and radial depth of cut at Work piece 1. Providing the same radial depth of cut, the straight cutting is repeated for the same direction. After cutting at Work piece 1 for approximately every 10m distance, cutting 3 passes at Work piece 2 for measuring the cutting force is performed. The shape of the won cutting edge at Work piece 1 is measured with a CCD-camera and a laser stylus unit. The cutting forces are measured at work piece 2. The above procedure is repeated until the tool life of the end mill is reached.

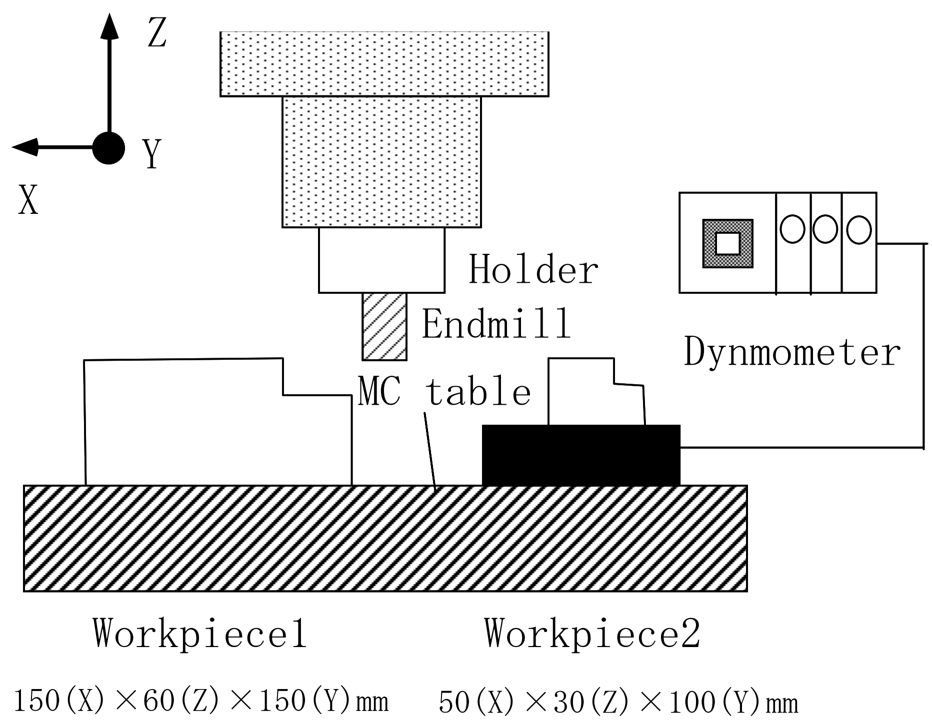

Figure 1: Setup for tool life test

3.3 Experimental results and analysis

Table 1 shows the cutting conditions for the tool life tests and the results (the tool life and the failure pattern) corresponding to each condition. Table 2 shows the input variables

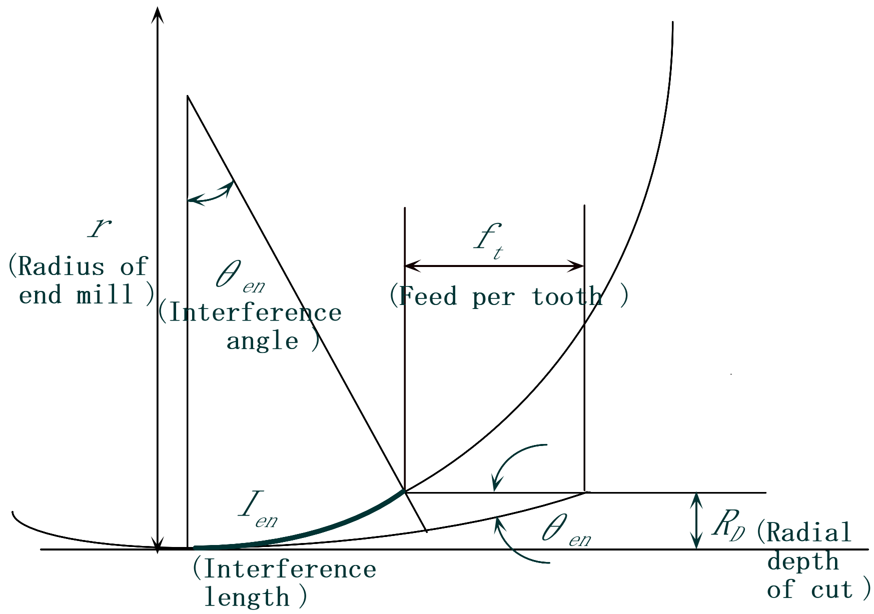

Figure 2: Interference length

introduced to the mathematical model in section 2 and the failure patterns. In the table the number of cutting is determined by the tool life, spindle speed and feed rate, the interference length is obtained using the following equation from Fig. 2, and the attrition length is given by the product of the number of cutting and the interference length.

$$l = r\theta = r \cdot \arccos\left(\frac{r - R_d}{r}\right) \tag{24}$$

The data in Table 2 are processed by the proposed simultaneous approach of the clustering and the multivariate data analysis techniques. The initial cutting force x_1, the maximum cutting force x_2, the number of cutting x_3, attrition length x_4 and Holm's value x_5 are chosen as predictor variables, and the tool failure patterns (progressive wear x_6, chipping x_7 and breakage x_8) as response variables. Choosing $\alpha = 0.1$ and $\beta = 0.5$ for the parameters, and $c = 2$ for the number of cluster, the processing results are shown in Tables 3 and 4. From these tables the data in the 1st cluster indicates that long attrition length leads to the progressive wear, the breakage is influenced by maximum cutting force being relatively low and the number of cutting has high correlation with the progressive wear. The distributions of the data points in two clusters are shown together with the projective axis in Figs. 3 and 4 respectively. From the results it is considered the discrimination method and its results to be adequate.

4. Conclusion

In machining hardened steel with (Al, Ti)N-coated micro-grain carbide end mill, to select the cutting conditions which lead to a tool life caused by the wear, a mathematical model for predicting the patterns of tool failure is identified, using Simultaneous approach of fuzzy cluster, principal components and multiple regression analysis. As the results the following conclusions are obtained.

1. A regression model is identified in which initial cutting force, maximum cutting force, attrition length and Holm's value are predictor variables and the tool failure patterns,

Table 1: Cutting conditions

Ex. no	Machine	Spindle speed rpm	Feed mm/min	Radial depth of cut mm	Axial depth of cut μm	Free length mm	Run out μm
1	1	9600	5760	0.5	10	30	2
2	2	9600	5760	0.5	10	30	3.8
3	3	9600	5760	0.5	10	30	4.5
4	1	9600	2880	0.5	10	30	4
5	2	9600	2880	0.5	10	30	3.8
6	3	9600	2880	0.5	10	30	3
7	1	9600	8640	0.5	10	30	2
8	2	9600	8640	0.5	10	30	3.2
9	3	9600	8640	0.5	10	30	2
10	1	9600	5760	0.75	10	30	4
11	2	9600	5760	0.75	10	30	2.5
12	3	9600	5760	0.75	10	30	4
13	1	9600	5760	1	10	30	5
14	2	9600	5760	1	10	30	4.5
15	3	9600	5760	1	10	30	3
16	1	9600	5760	0.5	10	50	8
17	2	9600	5760	0.5	10	50	5
18	3	9600	5760	0.5	10	50	4
19	1	4800	5760	0.5	10	30	5
20	3	4800	5760	0.5	10	30	4
21	2	9600	5760	0.5	15	30	5
22	3	9600	5760	0.5	15	30	4.8

Table 2: Predictor and response variables, and discrimination results

Ex. no	Intial cutting force N	Maximum cutting force N	Interference length mm	The number of cutting	Attrition length m	Holm's value Nm	Tool failure pattern	Discri mination result
1	548	1456	2.39	590×10^3	1410	141,292	Chipping	Incorrect
2	420	1336	2.39	593	1418	124,506	Wear	Correct
3	535	1406	2.39	533	1275	123,706	Wear	Correct
4	331	795	2.32	897	2080	117,119	Wear	Correct
5	382	626	2.32	1107	2567	129,400	Chipping	Correct
6	319	500	2.32	1113	2583	105,771	Chipping	Correct
7	687	1397	2.46	574	1413	147,248	Breakage	Correct
8	600	1566	2.46	847	2083	225,567	Wear	Correct
9	505	852	2.46	361	888	60,273	Breakage	Correct
10	425	1401	2.91	708	2061	188,192	Wear	Correct
11	620	1522	2.91	525	1528	163,622	Wear	Correct
12	528	1053	2.91	383	1116	88,180	Breakage	Correct
13	921	2324	3.35	230	771	125,014	Chipping	Incorrect
14	922	1326	3.35	175	586	65,895	Chipping	Correct
15	854	1040	3.35	223	748	70,851	Chipping	Incorrect
16	522	710	2.39	1817	342	267,457	Chipping	Correct
17	550	722	2.39	1358	3246	206,472	Breakage	Correct
18	363	909	2.39	602	1438	91,456	Wear	Correct
19	742	1195	2.53	373	945	91,478	Fracture	Incorrect
20	660	700	2.53	267	675	45,877	Breakage	Correct
21	576	1486	2.39	600	1434	147,845	Chipping	Correct
22	552	1299	2.39	787	1880	174,006	Wear	Correct

Table 3: Elements of eigenvectors in the intermediate variables

Cluster	Predicter variable	Intermediate variable	
		z_1	z_2
1	Initial cutting force	0.136	0.904
	Maximum cutting force	**-0.254**	-1.168
	Number of cutting	-0.174	-0.567
	Interference length	**0.294**	**-0.354**
	Holm's value	**-0.042**	**0.488**
2	Initial cutting force	-0.084	**0.284**
	Maximum cutting force	-0.398	0.050
	Number of cutting	**-0.195**	4.079
	Interference length	**-0.067**	-3.791
	Holm's value	**0.323**	-0.397

Table 4: Correlation coefficients with the intermediates variables

	1st cluster		2nd cluster	
	z_1	z_2	z_1	z_2
Wear	-0.273	-0.025	-0.417	-0.178
Cihpping	0.222	-0.078	-0.050	0.083
Breakage	0.234	0.250	0.183	-0.018

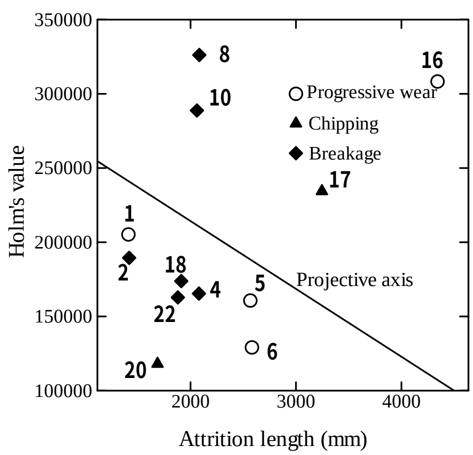

Figure 3:Distribution of the data in clister1

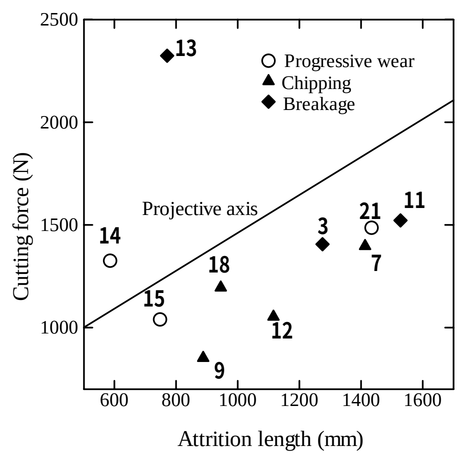

Figure 4:Distribution of the data in clister2

that is, progressive wear, chipping and breakage are response variables.

2. Using the model good results of the discrimination can be obtained, and therefore it is possible to select the cutting conditions which lead to a tool life caused by the progressive wear.

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