

An End-milling Condition Decision Support System Using Data-Mining for Difficult-to-cut Materials

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Abstract. We proposed the data-mining methods using hierarchical and non-hierarchical clustering methods to help engineers decide appropriate end-milling conditions. The aim of our research is to construct a system that uses clustering techniques and tool catalog data to support the decision of end-milling conditions for difficult-to-cut materials. We used variable cluster analysis and the K-means method to find tool shape parameters that had a linear relationship with the end-milling conditions listed in the catalog. We used the response surface method and significant tool shape parameters obtained by clustering to derive end-milling condition. Milling experiments using a square end mill under two sets of end-milling conditions (conditions derived from the end-milling condition decision support system and conditions suggested by expert engineers) for difficult-to-cut materials (austenite stainless steel) showed that catalog mining can be used to derive guidelines for deciding end-milling conditions.

Introduction

The demand for high-speed, high-efficiency, high-accuracy processing continues to grow due to the increasing need for quick machining and delivery of workpieces with a variety of complicated shapes. However, the processing and end-milling methods commonly used are not appropriate for many difficult-to-cut materials such as Ni-base superalloy, titanium alloy, and carbon fiber reinforced plastic, which are used extensively in aerospace. Such materials generally have high strength-to-weight ratios, high corrosion resistance, high strength retention ability at elevated temperatures, and low thermal conductivity. These characteristics can result in uneven tool wear and chatter vibration. Therefore, deciding the appropriate end-milling conditions is more difficult for difficult-to-cut materials than for other materials. There has been much research on the high-speed milling of these materials, and effective end-milling conditions [1], end-mill tool shapes [2], and processing methods have been reported [3]. Yamane and Sekiya [4] proposed a difficult-to-cut rating that can be calculated from the mechanical and thermal properties of the workpiece and used to estimate the difficulty of processing considering only the properties of the workpiece. However, it is still difficult to determine the appropriate end-milling conditions. Since there have been few reports of systematically obtained comprehensive information useful for determining appropriate end-milling conditions and processing methods, it is difficult to present standard end-milling conditions for difficult-to-cut materials. Even

though tool makers design tool shapes in much the same way, the end-milling conditions they recommend in their tool catalogs, which affect processing efficiency and cost, differ among makers due to differences in the coating base material coatings and edge angles they develop. There are thus no clear guidelines for deciding the end-milling conditions. A system for helping engineers decide the end-milling conditions would therefore speed up production and help reduce manufacturing costs. We previously

proposed using data-mining of tool catalog data as part of a system supporting the decision of end-milling conditions [5]. Using end-milling conditions derived from this system, we experimentally validated the effect of combining hierarchical and non-hierarchical clustering methods for milling JIS SKD61 die steel [6]. This system is targeted at deciding the conditions for die machining. We have now developed a system using data mining that supports the decision of end-milling conditions for difficult-to-cut materials. Testing using JIS SUS310S austenite stainless steel under end-milling conditions derived from the system showed that catalog mining can be used to derive guidelines for deciding end-milling condition.

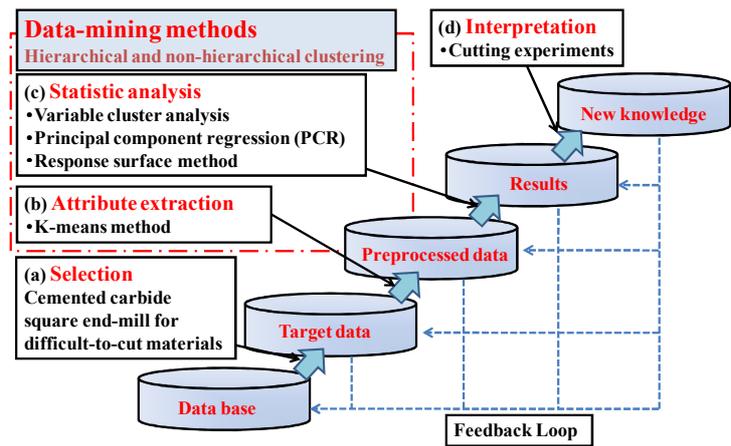


Fig. 1 Catalog-mining process.

Data mining

The data-mining process starts with data acquisition, selection, and cleansing. An analyst checks the data directly and removes any noisy data on the basis of judgment and experience. This removal of inaccurate or corrupt data is done in the data-cleansing step, which is said to account for the largest portion (70 to 80%) of the effort involved in the data-mining process.

Catalog-mining process. In the work reported here, we used end mill catalog data as the database. Such data are typically obtained on the basis of trial and error by cutting-tool makers during testing to identify appropriate end-milling conditions. These data are thus both sophisticated and numerical meaning that we could omit a large part of the data cleansing. The flow of the catalog-mining process we used is shown in Fig. 1. The algorithms used for the clustering and statistical analysis are described in detail elsewhere [5-6]. We used the K-means method, a non-hierarchical clustering method, to make clusters and extract attributes from the viewpoint of end mill tool shapes. This was done using Visual Mining Studio software (Mathematical Systems, Inc.). We used variable cluster analysis, a hierarchical clustering method, to visualize the data structure using tree diagrams, and we used principal component regression (PCR), to quantify the correlation between the objective and predictor variables. We developed equations for deciding the end-milling conditions by using the response surface method, which uses significant variables derived from variable cluster analysis and PCR. Several end-milling experiments were conducted to validate the equations.

Analysis results and discussion

Acquisition of data. The tool used was square end mills listed in the catalog of the largest tool maker in Japan. The catalog has a total of 825 pieces of data on cemented carbide square end mills related to their end-milling conditions for difficult-to-cut materials. For our database, we assumed a mill diameter of 0.1-25 mm. The catalog contains mill diameter D , cut length l , overall length L , shank diameter D_s , number of flutes z , shape data such as helix angle θ , and the tool coating material. Equivalent diameter D_e was calculated in terms of the number and weight of the flutes [5-6]. All the

shape variables were assumed to be predictor variables. These predictor variables were selected so that engineers could quickly determine the appropriate end-milling conditions from the shape of the square end mills. The work materials were composed of Ni-base superalloy (Inconel 718) (17%), titanium alloy (Ti-6Al-4V) (43%), and austenite stainless steel (JIS SUS304 and SUS316) (40%) up to *HRC*35-45 hardness. Hardness was used as a predictor variable. As criterion variables, we used the recommended end-milling conditions [spindle revolution *S* (rpm), table feed speed *F* (mm/min), and depth of cut]

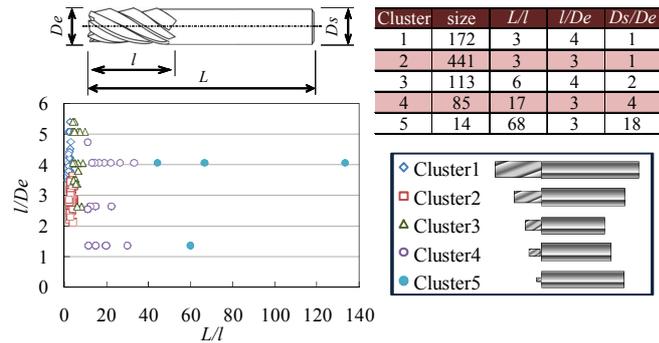


Fig. 2 Results of K-means method.

The values for these variables were input into the NC program. We therefore made the criterion variables cutting speed *V* (m/min), feed rate *f* (mm/tooth), and axial depth of the cut *Ad* (mm). These are important processing condition factors in side milling and slotting. *V* and *f* are defined as $V = \pi D S / 1000$ and $f = F / (S \cdot z)$, respectively. We further used the radius depth of the cut *Rd* (mm) as a criterion variable for side milling.

Modeling of cutting tool shape. Figure 2 shows a diagram of an end mill, the results obtained with the K-means method, the distribution map for each cluster for *l/De* against *L/l*, and the representative shape of each cluster. We used three variables, *L/l*, *l/De*, and *Ds/De*, to visualize the shape of the end mill. Once these variables were fixed, we could decide on the external shape of the square end mill. We set the number of clusters to five. The larger the *L/l* and *Ds/De*, the smaller the outside diameter. The smaller the *l/De*, the greater the number of flutes *z*. Clusters 4 and 5 consisted of small-diameter shaped end mills, and Clusters 1, 2, and 3 consisted of general rod-shaped end mills. The amount of data for Cluster 2 accounted for 53% of the total data. End mills that can conduct high-speed cutting are included in this cluster. These end mills have 4 or 6 flutes, more than other end mills. These results are consistent with those previously reported [5-6]. Furthermore, each cluster could be divided into ones of two types of processing: side milling and slotting.

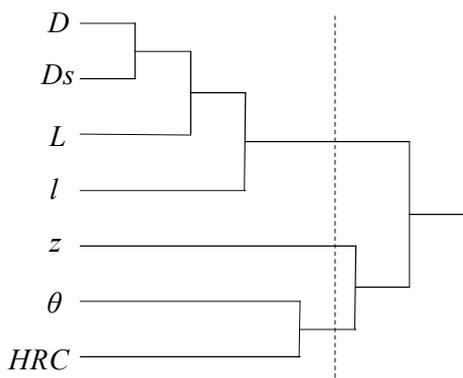


Fig. 3 Dendrogram of Cluster 2 for side milling.

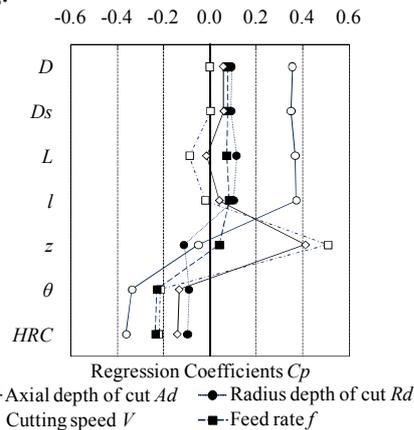


Fig. 4 Calculation result of PCR

Predictor variable selection. We applied variable cluster analysis and PCR to each cluster classified by the K-means method from the viewpoint of end mill shape. Example results of variable cluster analysis and PCR for Cluster 2 for side milling (typical shape) are respectively shown in Figs. 3 and 4. From Fig. 3 (a dendrogram), we can visualize the correlation between variables by focusing on the left clusters, which are marked off with a dashed line (cutting line). The closer the clusters combine to the left, the higher the correlation. The variables for side milling for Cluster 2 are divisible into three clusters: (*D*, *Ds*, *L*, and *l*), *z*, and (*theta*, *HRC*). The (*D*, *Ds*, *L*, and *l*) cluster correlates with the end mill

shape parameter. Helix angle θ is correlated with HRC . Number of flutes z is a sovereign variable. From Fig. 4, we see that cutting speed V has a positive relationship with z (C_p , 0.45) and a negative relationship with θ and HRC (C_p , -0.22). While the axial depth of cut Ad has a positive relationship with the end mill shape parameters (C_p , 0.38) and a negative relationship with θ and HRC (C_p , -0.35), Rd has no relationship with any of the predictor variables. These results show that Rd does not depend on the tool shape parameter and HRC listed in the tool catalog. Using these figures, we selected the predictor variables which used for the end-milling condition decision equations.

Derivation of end-milling condition decision equations. We derived ternary second-order polynomial response surface equations for deciding the end-milling conditions by using the variables determined to be significant using the response surface method, a practical optimization method. The ones for Cluster 2 for side milling are shown below.

$$Ad(R^2_{ad} 0.93) = 3z + l + 0.35Dz - 0.31Dl - 0.28zl + 0.29D^2 + 0.075l^2 - 15 \quad (1)$$

$$Rd(R^2_{ad} 0.75) = 0.75D - 0.24l + 1.17HRC + 0.019Dl - 0.17DHRC + 0.0058lHRC - 0.017D^2 - 0.0052l^2 - 0.015HRC^2 - 23 \quad (2)$$

$$V(R^2_{ad} 0.79) = 5D + 129z + 75HRC - 0.6Dz - 1.7zHRC - 0.09D^2 - 3z^2 - HRC^2 - 1657 \quad (3)$$

$$f(R^2_{ad} 0.72) = 0.022D - 0.0040l + 0.042HRC - 22 \times 10^{-5} DHRC - 34 \times 10^{-6} D^2 - 57 \times 10^{-6} l^2 - 53 \times 10^{-5} HRC^2 - 0.82 \quad (4)$$

To evaluate the accuracy of a prediction model, we have to compare the residual per unit freedom. In general, adjusted R-squared (R^2_{ad}) is used for judging accuracy. We used a T-test of the regression coefficient to determine the significance of each coefficient. On the basis of the results, the model was optimized by adding or deleting coefficients through stepwise elimination. Significant variables used in each equation are D , l , z , θ , and HRC . These variables are also significant in deciding the square end-milling conditions for die machining [5-6]. Application of the adjusted R-squared results made each equation more accurate than ones derived from multiple regression analysis. This was especially true for V and f , which have

velocity dimensions and showed low determination coefficients in previous studies [5-6]. The values from catalog mining are plotted against those estimated from the catalog cutting speed in Fig. 5. The catalog-recommended V can be divided into two ranges: 20-40 m/min for Inconel718 milling and 30-150 m/min for JIS SUS304 and Ti-4Al-6V milling. As shown in Fig. 5, the V given by Eq. (3) is 10-70 m/min for Inconel718 milling and 10-150m/min for JIS SUS304 and Ti-4Al-6V milling. When the estimated value was ~ 80 m/min, the range and data number of catalog recommended condition are widest and largest in other estimated value. Therefore, we have to validate the utility of the estimated values in this range.

Experimental validation of equations

End-milling conditions and experimental set-up. The cutting force, cutting temperature, workpiece ductility, and chip treatability are generally important as evaluation indicators of milling difficulty [4]. Engineers often decide the end-milling conditions and processing method on the basis of cutting force and temperature. To validate our equations, we conducted milling experiments under conditions:

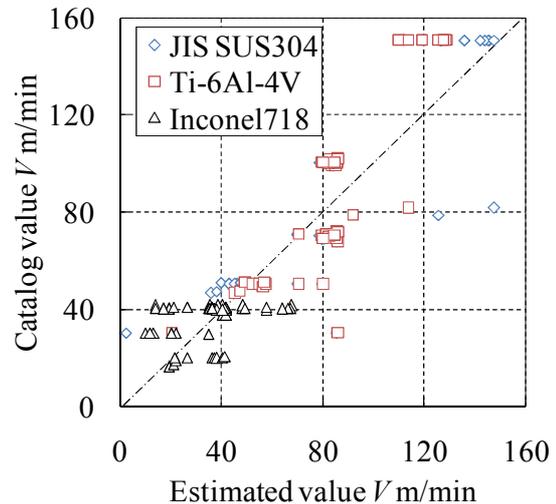


Fig. 5 Relationship between catalog value and estimated value.

Table 1 End-milling conditions.

	Mined condition			Standard condition		
	1350	2700	5400	715	1430	2860
Spindle speed rpm	1350	2700	5400	715	1430	2860
Table Feed mm/min	270	540	1080	140	280	560
Cutting speed V m/min	43	85	170	23	45	90
Feed rate f mm/tooth	0.05			0.05		
Axial depth of cut Ad mm	15			20		
Radius depth of cut Rd mm	1.0			1.0		
MRR cm^3/min	4	8	16	3	6	12

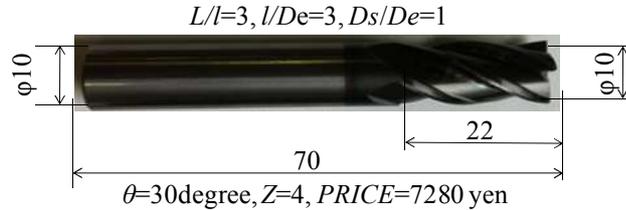


Fig. 6 Tool shape parameter of square end mill.

derived from data mining (mined conditions) and under standard end-milling conditions suggested by engineers (standard conditions). The workpiece was a $100 \times 100 \times 50$ mm sheet of heat-resistant steel (JIS SUS310S, 25Cr-20Ni, HRC35). We used a TiAlN-coated $\phi 10$ general-purpose square end mill that catalog recommended and appropriate end-milling conditions for JIS SUS310S are unknown. The tool shape is shown in Fig. 6. This end mill belongs to Cluster 2. Table 1 lists the mined conditions obtained by substituting the tool parameters into Eqs. (1)-(4) and the standard conditions. The Ad under the mined conditions was 25% less than under the standard ones. The material removal rate (MRR , cm^3/min) is defined as $MRR = F \cdot Ad \cdot Rd / 1000$. The experiments involved processing (down-cut in one pass direction) a flat surface. The machine tool was an ACCUMILL4000 (made by Mori Seiki). The tool extension was 30 mm. The cuttings were made under dry air and minimal quantities of lubricant (MQL) (Blube LB-1 Fujigiken Inc. 6cc/h) condition. An infrared radiation thermometer with thermographic resolution of 0.03 K (H2640 NEC/Avio) was used to measure the cutting temperature. The emissivity of the measurement surface was set to 0.43 for dry air cutting and to 0.80 for MQL cutting. The cutting speed was varied by cutting it in half and doubling it for each condition (see Table 1).

Results and discussion. Fig. 7 shows a thermal image of dry milling under standard conditions. From such images, we can photographically analyze not only the blade temperature of the end mill and the temperature increase of the shank part and workpiece but also the temperature and fly appearance chip. Fig. 8 shows the maximum cutting temperature as shown in Fig. 7 for the different end-milling conditions. We can see that maximum temperature can be reduced 30 to 50% by using MQL under both conditions. Under the standard conditions, the maximum temperature and thermal gradient due to saturation were higher than under the mined conditions. Under the mined conditions for V set to 170 m/min, the maximum temperature did not rise rapidly and was almost the same as for V set to 85 m/min. However, chatter vibration arose under the mined

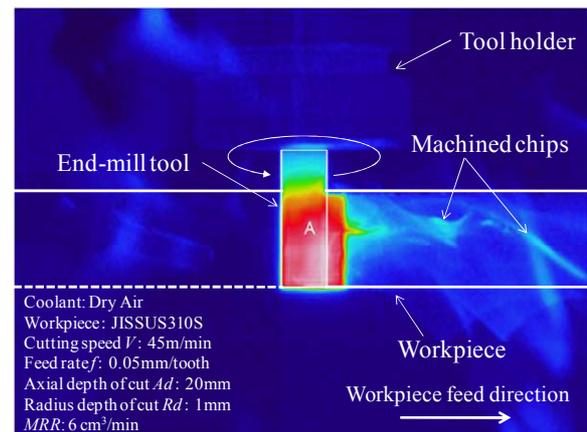


Fig. 7 Thermal image of dry cutting under standard conditions.

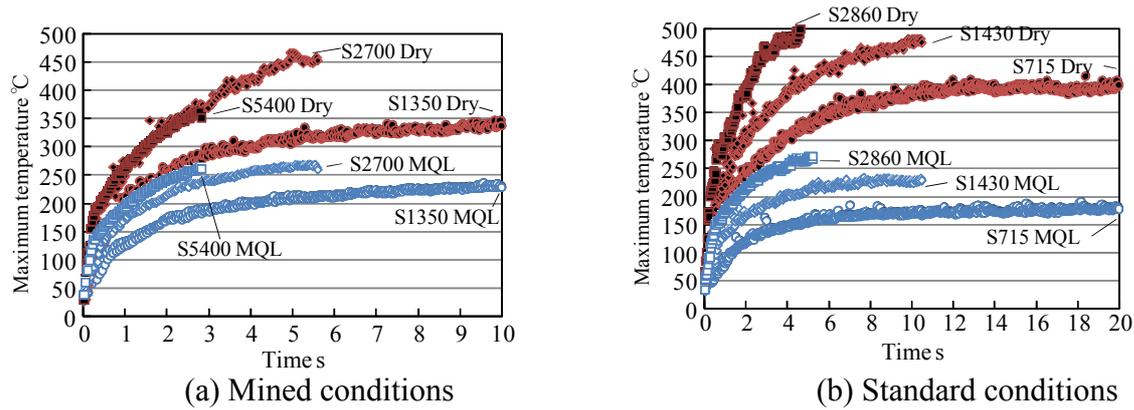


Fig. 8 Maximum temperature for different end-milling conditions.

conditions for V set to 170 m/min for both the dry air and MQL condition. Therefore, these conditions are not practical. No wear was observed on the end mill blade under the mined conditions except for V set to 170 m/min. Figure 9 shows the relationship between the saturated maximum tool temperature in Fig. 8 and MRR for the different end-milling conditions. The maximum temperature differed greatly between the mined and standard conditions at each MRR . The use of MQL effectively reduced the cutting temperature at each MRR . Near the crossover point of the dashed and solid MQL curves, the maximum temperature for a specific MRR value can be reduced by choosing more effective end-milling conditions.

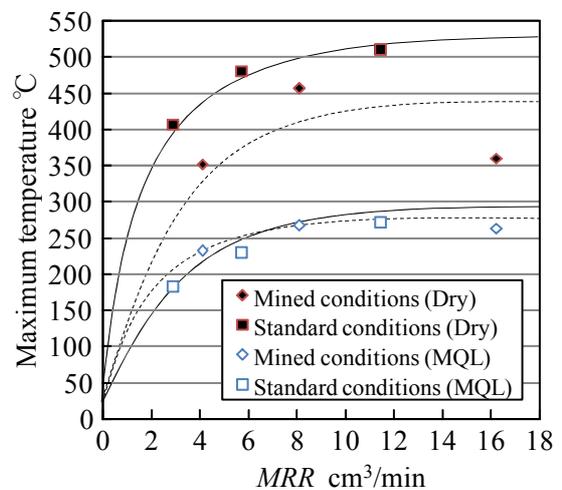


Fig. 9 Thermal image of dry cutting under standard conditions.

Conclusion

Catalog mining, which is an application of hierarchical and non-hierarchical clustering methods can be used as part of a decision methodology for difficult-to-cut end-milling conditions. We found that catalog mining can be used to derive guidelines for deciding end-milling conditions. Measurement of the milling temperature using an infrared radiation thermometer and examination of the analytical method of the thermal imaging confirmed that using an MQL condition reduced the maximum tool temperature during milling. The guidelines derived from catalog mining are found to be more effective under a severe condition such as dry air coolant.

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