A study of factors affecting the performance of micro square endmills in milling of hardened tool steels


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Abstract

Proper setting of cutting conditions is critical for the performance of micro endmills in micro milling of hardened tool steels. In this paper, the influence of the cutting parameters on the wear behaviour of micro square endmills is presented. The selected parameters are cutting speed, depth of cut, and feed per tooth; Central Composite experimental Design (CCD) was used for a statistical analysis of the influence of these parameters. A quadratic model was fitted to describe the performance of the tool wear; the ANOVA analysis shows that the quadratic model gives a good prediction of the experimental results. On considering the magnitudes of the coefficients it is seen that the feed per tooth has a greater influence on the tool wear than cutting speed and depth of cut within the tested process window. By applying this method, the micromilling process can be planned to achieve an optimum tool wear performance for a tool-workpiece combination.

Keywords: micromilling, tool wear, design of experiments

1. Introduction

Direct machining of hardened tool steel by micro endmills has great advantages over EDM process in throughput time and manufacturing cost for the dies and moulds industry to produce micro moulds or macro moulds with micro features. However, as found in former experiments [1], the severe tool wear and premature breakage of micro endmills become the bottleneck for the development of this technology and make it difficult to apply micromilling in industry. Due to the tool problems, the workpiece quality is not satisfying requirements in terms of burr formation, surface quality and form accuracy.

There are several reasons for the poor performance of micro endmills, such as unsuitable tool geometry, unknown cutting conditions, lack of knowledge in machine tools, machinability of workpiece material, and wrong milling strategies. Among all these aspects, the cutting conditions play an important role for the tool wear/breakage. In [2] it was reported that the error in depth of cut led to tool breakage. On the one hand, because of the scaling effect, the micro cutting tools become vulnerable to excessive cutting conditions; big cutting force will break the tool directly from first contact. On the other hand, the process parameters for micromilling of hardened tool steel are unknown. There is no handbook available for micromilling as a reference. At this moment the selection of cutting parameters are mainly from the recommend values by tool suppliers, which are mostly based on trial and error practice.

Statistical design of experiments (DOE) is an efficient method for planning experiments so that the data obtained can be analyzed to yield valid and objective conclusions. [3] Well chosen experimental designs maximize the amount of “information” that can be obtained for a given amount of experimental effort. Moreover, the significant input variables can be identified through a proper design; therefore the process can be optimized in terms of the response.
workpiece coordinate setting.

The used cutting tools were 2-flute TiAlN coated Ø 0.5mm square carbide endmill, as shown in Fig. 2. The cutting length is 0.8mm; the helix angle is 30º. The cutting edge radius was checked by making a cross section of the cutting tool; the result is about 2µm. For comparison, these endmills were produced from same batch to avoid quality variation. Minimum Quantity Lubrication was used. The workpiece material is Böhler W300 (SAE H11) with 54 HRC; its chemical composition (%) is: C 0.37, Si 1.18, Mn 0.35, P < 0.005, S 0.004, Cr 5.01, Mo 1.29, V 0.32. The dimension of the workpiece is 20×20×10mm (L×W×H). The surfaces of the workpiece were ground at forehand to achieve a good flatness.

To exclude the influence of complex geometries, simple slot milling was chosen to test the tool wear behaviour of the micro endmill. For a fair comparison, same amount of workpiece material (20mm³) was removed at each different combination of cutting conditions; tool wear was measured after machining. The dynamic runout at the cutting tool tip was measured by drilling a hole in resin under same speed as the test and checking the diameter of the drilled holes afterward. Stability of the process was checked by examining the milled surface, which was not a problem. The tool wear was measured by Keyence VHX-100 microscope and FEI Quanta 600 Scanning Electron Microscope; the resolution of the pictures is about 0.3µm/pixel, which depends on the magnification of the lens. Cutting force was monitored by Kistler MiniDyn 9256C2. The workpiece quality was checked by Mitutoyo Surftest 500 and WYKO NT 3300 white light interferometer.

2.2. Experimental design

In this research, Central Composite Design (CCD) is adopted to study the relation between cutting conditions (cutting speed \( v_c \), depth of cut \( a_p \), and feed per tooth \( f_z \)) and the wear of micro endmills, and to optimize the cutting conditions in order to plan the cutting conditions to achieve an optimum tool performance. Because it was known that micro tools show different dominant wear type/mechanism from conventional endmills [1], a quadratic relation is first assumed, and the interaction between input variables cannot be excluded at forehand.

CCD is an efficient design method for fitting second-order response surface equation. By proper choice of the number of centre points, the design will have some beneficial properties, such as orthogonality, rotatability, and uniformity of precision [6]. In this study, 6 centre points are used. Each input variable has 2 levels, so there are altogether 8 \((2^3)\) factorial points. Besides the 6 augmented points, there are 20 \((8+6+6)\) experiments in total. The selection of levels for the input variables was based on former experiments; the maximum \( v_c \) is limited by the achievable spindle speed. The coded design variables are shown in Table 1.

### 3. Results and discussion

#### 3.1. Tool wear type and measurement

During tests, no tool breakage happened under the tested conditions. Fig. 3 gives an example of the wear of the tested Ø0.5mm square endmill, both top view and side view. From this figure, it is seen that the main wear type of the micro endmill is the fracture of the two cutting edge corners, which changes the geometry of the endmill largely. For conventional endmills, the flank wear is normally used as the tool wear criteria; however from the side view of the worn micro endmill, it is clear that the flank wear is not dominant, and difficult to measure, because of which it cannot be used here to evaluate the wear of the micro endmill. Therefore, it is decided in this study that the wear of the micro endmill is defined as the reduction of the tool cutting diameter at the end face of the cutting tool.

The result of the tool wear measurement is shown in Fig. 4. The quality of the tool wear data was checked by 4-plot, namely Run sequence plot, Histogram plot, Lag plot, and Normal probability plot. The 4-plot showed that the process is in statistical control.

<table>
<thead>
<tr>
<th>Coded variables ( x_i )</th>
<th>Input variables</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>( v_c ) (m/min)</td>
</tr>
<tr>
<td>-1.68</td>
<td>20.73</td>
</tr>
<tr>
<td>-1.00</td>
<td>31.42</td>
</tr>
<tr>
<td>0.00</td>
<td>47.12</td>
</tr>
<tr>
<td>1.00</td>
<td>62.83</td>
</tr>
<tr>
<td>1.68</td>
<td>73.51</td>
</tr>
</tbody>
</table>

Fig. 4. Tool wear measurement result.
Therefore, these data can be used for further analysis.

3.2. Analysis of the results

A quadratic model is proposed to describe the relation between input variables and the response. The coefficients of the quadratic model were fitted by least square method. After regression, the model is:

\[ \hat{y} = 131.65 + 0.25v_c - 15.32f_z + 0.01v_c^2 + \frac{1444.64}{a_p} + 1.41f_z^2 - 4.91v_c f_z - 0.09v_c f_z^2 - 55.78a_p f_z \]  

where \( \hat{y} \) is the estimated yield, \( v_c, a_p, \) and \( f_z \) are input variables. The \( R^2 \) measures how well the regression fits the observed data. In this case, the \( R^2 \) is 0.9767, which shows that the model explains 97.67% of the variability in tool wear behaviour.

The result of ANOVA analysis is shown in Table 2, which gives the statistical significance of the regression by comparing the mean square of regression against the estimated value of the pure error. The F regression is 59.18, which is much bigger than the critical value of significance value at 5% level \( F(9/5) = 4.77 \). This means that the yield of the experiments can be well described by a quadratic function. The F lack of fit is 1.54, which is smaller than the critical value of F test at 5% level F (5/5) = 5.05; therefore no important terms are missing or misspecified in the functional part of the model.

In Eq. 1, the sign of the coefficients show the positive or negative influence of the input variable on tool wear. For example, for the main effects, the coefficient of \( v_c \) is positive, which means that the tool wear will increase with the increase of \( v_c \). The coefficients of \( a_p \) and \( f_z \) are negative, which means that the tool wear magnitude will decrease with the increase of these variables. However the influence of the input variables is complicated by their interaction and the quadratic terms. Besides not all of these terms have same significant effect on the response.

The significance of all the coefficients in Eq. 1 was tested by observed t-test; it was done by dividing the absolute value of the coefficient value by the standard value of the coefficient. The observed t-result was compared with the critical t-value to decide if this coefficient is statistically different from zero. If the absolute value of the observed t-result is much greater than the critical t-value, it can be concluded that this coefficient is statistically significant. Otherwise the coefficient is not statistically different from zero; it can be omitted from the equation and its effect is pooled into the error term. The result of the t-test is that the \( f_z \) and its quadratic term, and the interaction \( v_c f_z \) and \( a_p f_z \) have significant effect on the tool wear; all other terms can be omitted. The adjusted tool wear model is shown in Eq. 2. The \( R^2 \) value of the new model is 0.96.

### Table 2

<table>
<thead>
<tr>
<th>Source</th>
<th>d.f.</th>
<th>SS</th>
<th>MS</th>
<th>F</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total</td>
<td>8222.25</td>
<td>19</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Regression</td>
<td>8031.04</td>
<td>9</td>
<td>892.34</td>
<td>59.18**</td>
</tr>
<tr>
<td>Lack of fit</td>
<td>115.81</td>
<td>5</td>
<td>23.16</td>
<td>1.54</td>
</tr>
<tr>
<td>Pure error</td>
<td>75.39</td>
<td>5</td>
<td>15.08</td>
<td></td>
</tr>
</tbody>
</table>

**Significant at the 5% level.

Fig. 5. Interaction plot of the response surface model.

Fig. 6. Effect of input variables on tool wear.
Fig. 5 is the interaction fit and plot of the response surface model. Each plot shows the fitted relationship of the tool wear to the independent variable at a fixed value of the other two independent variables. The first plot has \( v_c \) as the independent variable. The second and third plots have \( a_p \) and \( f_z \) respectively. The 95% confidence intervals are also plotted on this figure.

From Fig. 5, it can be seen that within the tested process window, the tool wear decreases with the increase of the \( v_c \) and \( a_p \). As described in the section 2, the material removal was kept same for each cutting condition set, the higher the cutting speed, the shorter the machining time; therefore it is reasonable to see the trend of decreasing tool wear with increasing \( v_c \). Another reason for this observation could be that the tested speed range is limited by the spindle speed; the critical \( v_c \) for severe tool wear is not within the range of the test. When increasing \( a_p \), the unit force on the cutting edge is kept same, but the machining time is short, so it is beneficial for the tool wear.

The effect of \( f_z \) has different effect on the tool wear from \( v_c \) and \( a_p \). From Fig. 5, it can be seen that the tool wear magnitude decreases with the increase of \( f_z \) until a certain level, then further increase of \( f_z \) will lead to increase of tool wear. This is because that the increase of \( f_z \) will increase the unit force on the cutting edge. When \( f_z \) is above a critical value, the stress on the cutting edge corner will be too big and the cutting edge will be broken.

In Fig. 6 the relation between the input variables and the tool wear can be further studied. Fig 7 shows the tool wear at different cutting conditions.

From Fig. 5-6, it is seen that there exists an optimum value for \( f_z \) to achieve a minimum tool wear value when \( v_c \) and \( a_p \) are fixed. For example, when \( v_c \) is 62.83m/min (coded 1), \( a_p \) is 0.10mm (coded 1), the tool wear achieves a minimum value of 13.67µm at \( f_z \) of 9.51µm. By applying this method, the cutting conditions can be planned to achieve minimum tool wear for a tool-workpiece combination.

4. Conclusions

Design of experiment is used to study the effect of cutting conditions on tool wear in micromilling of hardened tool steel. It was observed that micro endmills show different wear type from macro endmills. From the ANOVA analysis of the magnitudes of the coefficients, \( f_z \) has a greater effect on the tool wear than that of cutting speed and depth of cut within the tested range. From the interactive response surface model plot, it is seen that there exists an optimum \( f_z \) value that achieves a minimum tool wear when \( v_c \) and \( a_p \) are fixed. By applying this method the cutting conditions can be planned to achieve an optimum tool wear under a tool-workpiece combination.

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References


