Optimization of the Process Parameters for Micro-Milling Thin-Walled Micro Parts Using Advanced Algorithms

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Optimization of the process parameters for micro-milling thin-walled micro parts using advanced algorithms

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Abstract

The surface integrity and machining accuracy of thin-walled micro parts are significantly affected by micro-milling parameters mostly because of their weak stiffness. Furthermore, there is still a lack of studies focusing on parameters optimization for the fabrication of thin-walled microscale parts. In this paper, an innovative approach is proposed for the optimization of machining parameters with the objectives of surface quality and dimension accuracy, which integrates the Taguchi method, principal component analysis method (PCA) and the Non-dominated sorting genetic algorithm (NSGA-II). In the study, surface arithmetic average height $S_a$, surface root mean square height $S_q$, and 3-D fractal dimension $D_s$ are selected to evaluate surface quality. Then micro-milling experiments are conducted based on the Taguchi method. According to the experimental results, the significance of machining parameters can be determined by range analysis. Besides, regression models for the responses are developed comparatively, and the PCA method is employed for dimension reduction of the optimization objective space. Finally, two combinations of machining parameters with the highest satisfaction are obtained through NSGA-II, and verification experiments are carried out. The results show that the surface quality and dimension accuracy of the thin-walled microscale parts can be simultaneously improved by using the proposed approach.

Keywords: thin-walled microscale parts; micro-milling; fractal dimension; principal component analysis; advanced optimization algorithms.
1. Introduction

Usually, the microscale is defined as 1μm-1000μm in the field of mechanical processing\textsuperscript{[1]}. Thin-walled microscale parts refer to the component structures with characteristics of microscale size and a height-to-thickness ratio greater than 5. Thin-walled microscale parts are increasingly in demand in many fields, including microelectrodes, microfluidic devices, micro/miniature dies and moulds \textsuperscript{[2, 3]}. Micro-milling has the advantages of high production efficiency and high processing accuracy. Therefore, it is increasingly used in the processing of thin-walled microscale parts. However, both the thin-walled microscale part and micro-milling tools have weak stiffness, which brings challenges for its fabrication, especially for difficult-to-machine materials like Ti-6Al-4V alloy \textsuperscript{[4]}. So, it is necessary to further investigate the machining process of thin-walled microscale parts.

Low surface quality and dimensional error are common problems in the processing of thin-walled microscale parts. An effective way to address these problems is to investigate the effects of machining parameters on processing quality and obtain the optimal parameters using an appropriate optimization method. Based on finite element analysis and response surface method (RSM) experiments, the effects of machining parameters were analyzed, and spindle speed and radial depth of cut were found as the most important factors for the burr height in micro-milling of thin-walled structure \textsuperscript{[5]}. In thin wall fabrication, the effect of the axial depth of cut on the surface quality was found nonlinear \textsuperscript{[6]}. Previous research showed that the interaction of radial cutting depth and axial cutting depth significantly influences surface roughness \textsuperscript{[7]}. However, Kant \textsuperscript{[8]} pointed out the feed per tooth is the most important machining parameter to reduce surface roughness and power consumption, followed by the depth of cut and cutting speed. To characterize the surface quality comprehensively, the fractal dimension method is employed. It was found that the fractal dimension measured by the mechanical method and the optical method can characterize the surface topography well, and it had a good correlation with the roughness value \textsuperscript{[9]}. The surface of thin-walled microscale parts analyzed by three-dimensional fractal dimension $D_s$ had better results than the surface roughness $S_a$ and $S_q$ \textsuperscript{[10]}. Many researchers have endeavored to obtain optimal machining parameters. For improving machining quality, an optimization procedure based on the genetic algorithm and neural network was proposed to minimize surface roughness \textsuperscript{[11]}. A method for simultaneous optimization of the burr width and surface roughness was also proposed using Taguchi-based grey correlation analysis \textsuperscript{[12]}. Sahu and Ballav \textsuperscript{[13]} performed optimization balancing surface roughness and cutting force of the turning process. Artificial neural network and particle swarm algorithm were used for optimizing
cutting force and surface roughness at the same time, and verification tests were carried out. The results showed that both the cutting force and surface quality were improved significantly [14]. For machining efficiency and cost, a method integrated Taguchi method, response surface method and multi-objective particle swarm optimization algorithm was present for the objectives of specific energy consumption and processing time [15]. The machining parameters of the multi-pass turning operation were optimized by the genetic algorithm. The constraints of the model include tool life, cutting power consumption and cutting force. This method generated lower unit production costs compared with the previous results from the literature [16]. Cutting energy and material removal rate were optimized based on Taguchi's experimental design and signal-to-noise ratio [17]. The optimal parameters combination was determined for the minimum unit production cost through the colony algorithm [18]. In multi-objective optimization problems, different objectives are conflicting in nature. Optimizing one of the objectives may cause the deterioration of the others, and multi-objective optimization methods are easily trapped in local optimal solutions. NSGA-II is widely used for its good robustness and global search capabilities. Qu et al. [19] found that the NSGA-II has the best optimization performance in the multi-objective problem in the milling process of thin-walled structures. NSGA-II was used for minimizing the tool life and processing cost in the micro-milling process, and the obtained results were better than those in the previous literature [20]. For cutting Inconel 718, a method for the selection of optimal process parameters was proposed based on NSGA-II [21].

Due to the microscale size and low stiffness of thin-walled microscale parts, the errors of machine tools and cutting tools are more likely to be reflected on the workpiece, which makes the machining quality is more sensitive to the selection of machining parameters. However, most previous studies on the optimization of machining parameters focus on macroscale thin-walled parts. And fewer researches are performed with consideration of more than four objectives simultaneously in the micro-milling process. This paper firstly conducts orthogonal experiments for micro-milling thin-walled microscale parts. Then the effects of machining parameters on the optimization objectives are analyzed according to the obtained results. Besides, a method for the optimization of machining parameters using PCA-based NSGA-II is proposed. The optimal parameters for the best surface quality and dimension accuracy can be obtained through this method. Finally, micro-milling experiments are performed to verify the effectiveness of the proposed method.

2. Method and experiments
2.1 Procedure for the optimization of machining parameters

Fig. 1 depicts the flowchart of the machining parameters optimization for the thin-walled microscale parts. Dimensional error $D_e$, arithmetic average height $S_a$, root mean square height $S_q$, and surface fractal dimension $D_s$ are considered simultaneously in this work. The thin-walled part shown in Fig. 2 is fabricated by dry micro-milling. The workpiece material is Ti-6Al-4V, and the values for $b$, $h$ and $l$ are 100 $\mu$m, 600 $\mu$m and 5 mm, respectively. Firstly, experiments based on the Taguchi method are carried out. The surface topographies and dimensions of the machined parts are measured by white light interferometer (WLI) and coaxial image instrument (CII), respectively. Then multiple regression models are developed based on stepwise regression. Besides, the PCA is performed for dimension reduction. After that, cutting parameters are optimized by NSGA-II and the Pareto optimal solution set is obtained. Finally, two combinations of machining parameters with the highest satisfaction are selected for the verification experiments.
2.2. Optimization objectives

2.2.1 Surface roughness

The surface arithmetic average height $S_a$ and the surface root mean square height $S_q$ are selected to reflect the surface roughness. $S_a$ represents the average geometric error of the milled surface and $S_q$ represents the root mean square of the geometric error of the milled surface respectively. The calculation methods are shown as follows.

$$
S_a = \frac{\int \int_S \Phi(x, y) - \xi(x, y) dx dy}{S} \\
S_q = \sqrt{\frac{\int \int_S \Phi^2(x, y) dx dy}{S}}
$$

(1)

Where $\Phi(x,y)$ denotes the height information of the surface, and $\xi(x,y)$ corresponds to the reference plane of the surface.

2.2.2 3-D surface fractal dimension

The characteristics of the machined surface cannot be fully present by surface roughness. Therefore, the 3-D fractal dimension $D_s$ is employed to characterize the machined surface from the perspective of the surface structure. Among the 3-D fractal dimension calculation methods for the mechanical machining surface, the box-counting method has the best accuracy\(^{[22]}\). So, it is adopted as one of the key objectives of optimization. The box-counting method uses cubes with the same side length to segment the three-dimensional surface topography, and the minimum number of boxes covering the image surface is employed for calculating the fractal dimension. The fractal dimension can be expressed as Eq. (1).

$$
D_s = \frac{\ln N(\varepsilon)}{\ln(\varepsilon^{-1})}
$$

(2)

Where $\varepsilon$ represents the side length of the box, and $N(\varepsilon)$ represents the number of boxes.

2.2.3 Dimension error

The dimension error is the deviation between the actual dimension and the design dimension of the thin-walled structure in the thickness direction. As shown in Fig.3, deflection is inevitable due to the weak stiffness of the thin-walled micro part and micro-milling tool. The dimension error $D_e$ can be expressed as.

$$
D_e = |D_a - D_i|
$$

(3)

Where $D_a$ is the actual dimension, and $D_i$ is the design dimension.
2.3 Experimental design

As shown in Fig. 4, the micro-milling experiments are carried out on the KERN Evo five-axis vertical machining center. The cutting tool is a four-edged carbide end mill with a diameter of 1 mm and 45° helix angle, and the cutting strategy is dry milling. Tool wear has a significant influence on the machining process [23,24], in order to avoid the effects of tool wear on the machining results, a fresh tool is used in each experiment. The workpiece material is Ti-6Al-4V alloy.

In order to analyze the effects of machining parameters (spindle speed \( n \), feed per tooth \( f_z \), axial milling depth \( a_p \), and radial milling depth \( a_e \)) on machining quality, an orthogonal experiment is designed, ignoring the interaction among all the parameters. The Taguchi experiment table L16 (4\(^4\)) is chosen for experiment design, and the process parameters and their levels are shown in Table 1.

| Symbol | Process Parameters | Units       | Level 1 | Level 2 | Level 3 | Level 4 |
|--------|--------------------|-------------|---------|---------|---------|---------|
| A      | Spindle speed \( n \) | r/min      | 15000   | 20000   | 25000   | 30000   |
| B      | Axial depth of cut \( a_p \) | μm | 50      | 60      | 100     | 150     |
| C      | Radial depth of cut \( a_e \) | μm | 20      | 30      | 40      | 50      |
| D      | Feed per tooth \( f_z \) | μm/tooth | 0.5     | 1.5     | 2.5     | 3.5     |

2.4 Multi-objective optimization method using PCA-based NSGA-II
The non-dominated sorting genetic algorithm with elite strategy (NSGA-II) is a multi-objective evolutionary algorithm based on the non-inferior solution (Pareto) set. It has the characteristics of high optimization efficiency and good global searchability. Therefore, it has been widely used in the optimization of process parameters. But for the high-dimensional optimization objectives space with more than four functions, NSGA-II is incapable. Meanwhile, the visualization of results for high-dimensional objective space is rather difficult. So, the key step is to reduce the dimension of the 4-D optimization objectives space by means of principal component analysis (PCA).

3. Results and discussion

The results of the orthogonal experiments are shown in Table 2. When performing measurements, the results are averaged at three locations on the thin-walled parts.

| No. | Symbol | Control factors | Responses |
|-----|--------|-----------------|-----------|
|     | A B C D |                 | S_d(μm)  | S_q(μm)  | D_s(μm) | D_e(μm) |
| 1   | A1B1C1 | 15000 50 20 0.5 | 0.3153   | 0.4363   | 2.4534  | 1.4     |
| 2   | A1B2C2 | 15000 60 30 1.5 | 0.4617   | 0.5600   | 2.4083  | 9.5     |
| 3   | A1B3C3 | 15000 100 40 2.5 | 0.6920   | 0.9067   | 2.3982  | 4.6     |
| 4   | A1B4C4 | 15000 150 50 3.5 | 0.3433   | 0.4420   | 2.4174  | 3.3     |
| 5   | A2B1C2 | 20000 50 30 2.5 | 0.4087   | 0.5157   | 2.4119  | 11.2    |
| 6   | A2B2C1 | 20000 60 20 3.5 | 0.1120   | 0.1563   | 2.5037  | 3.9     |
| 7   | A2B3C4 | 20000 100 50 0.5 | 0.2270   | 0.2867   | 2.5012  | 3.3     |
| 8   | A2B4C3 | 20000 150 40 1.5 | 0.3217   | 0.3873   | 2.4509  | 4.2     |
| 9   | A3B1C3 | 25000 50 40 3.5 | 0.3373   | 0.4477   | 2.4112  | 8.7     |
| 10  | A3B2C4 | 25000 60 50 2.5 | 0.3873   | 0.5103   | 2.4070  | 4.1     |
| 11  | A3B3C1 | 25000 100 20 1.5 | 0.3670   | 0.4717   | 2.4085  | 2.1     |
| 12  | A3B4C2 | 25000 150 30 0.5 | 0.2327   | 0.3083   | 2.4762  | 0.1     |
| 13  | A4B1C4 | 30000 50 50 1.5 | 1.3740   | 1.8307   | 2.3968  | 2.1     |
| 14  | A4B2C3 | 30000 60 40 0.5 | 0.1823   | 0.2350   | 2.4557  | 8.4     |
| 15  | A4B3C2 | 30000 100 30 3.5 | 0.4407   | 0.5537   | 2.4149  | 3.6     |
| 16  | A4B4C1 | 30000 150 20 2.5 | 0.4987   | 0.6200   | 2.4100  | 11.5    |

3.1 Effects of machining parameters on surface roughness

Fig. 5 shows the variations of the three-dimensional roughness with machining parameters. The surface roughness decreases when the spindle speed increases from 15000 r/min to 20000 r/min. While, as the spindle speed exceeds 20000 r/min, the surface roughness shows an increasing trend. Generally, high spindle speed can lead to more heat generation, which can cause the thermal softening
effect on the Ti-6Al-4V material. However, the continuous spindle speed increase can cause rapid tool wear and enlarge cutting tooltips, which can change the material removal mechanism and deteriorate surface quality. The minimum surface roughness is found when the axial cutting depth is 60 μm. When the axial cutting depth is less than this chip thickness, the obvious ploughing and extrusion effect between the cutting edge and the workpiece can damage the surface quality. The surface roughness shows an increasing trend as the radial depth of cut increases. And a significant rise is observed when the radial depth of cut drops from 40 μm to 50 μm. In addition to the rise in cutting force, the stability of the tool-workpiece system goes down when the radial depth of cut increases, which can cause chatter and a significant deterioration of surface quality. The surface roughness reaches the largest value at 1.5 μm/tooth and it has a rapid decrease when the feed per tooth reaches 0.5 μm/tooth. The change in surface roughness presents an opposite trend compared to macro-scale milling when the feed per tooth increases from 1.5 μm/tooth to 3.5 μm/tooth. In Fig. 4, the change of $S_q$ is greater than that of $S_a$, which means that $S_q$ is more sensitive to the variations of machining parameters. And a combination of machining parameters for minimum surface roughness is obtained: $n=20000$ r/min, $a_p=60\mu m$, $a_e=20\mu m$, and $f_z=0.5\mu m/tooth$.

![Fig. 5 Main effects plot for $S_a$ & $S_q$](image)

3.2 Effects of machining parameters on 3-D fractal dimension

In Fig. 6, the variations of surface fractal dimension $D_s$ with machining parameters show an opposite trend with the surface roughness. In order to further discuss the relationship between the fractal dimension and surface roughness, the linear fit is performed between $D_s$ and $S_a$. Fig.7 shows the correlation between $D_s$ and $S_a$. An obvious negative correlation can be observed, which is consistent with the conclusions in previous literature $^{[22]}$. Therefore, a good surface quality means a small surface roughness and a big fractal dimension value.
However, the negative correlation between $D_s$ and $S_a$ is not a one-to-one correspondence. Fig. 8 shows four selected surface topographies in all the experimental results.

Comparing the surface topographies of the 7th and the 12th experiments, a conclusion can be drawn that when the surface roughness is close, the fractal dimension of the machined surface with defects is smaller. Surface topographies of the 3rd and the 13th experiments show that when the fractal dimension is close, the surface roughness may have an obvious difference. It can be seen, compared with the surface roughness, the surface fractal dimension is more sensitive to the defects of the machined surface. Therefore, the combination of surface roughness and surface fractal dimension has a better characterization performance.
3.3 Effects of machining parameters on dimension deviation

Fig. 9 shows the effects of micro-milling parameters on the workpiece actual size. As can be seen, the actual size of the thin-walled parts is greater than 100 μm, except for one group of the results. This is caused by the deflection during the machining process due to the weak stiffness of the micro-milling cutter and the thin-walled structure.

![Fig. 9 Main effects plot for Ae](image)

Fig. 10 shows the largest dimension error is at 30000 r/min. A larger spindle speed can cause rapid tool wear and increase the micro-milling force, which can enlarge the deflection of the thin-walled structure.
When the axial depth of cut is less than 60 μm, the ploughing and extrusion effects can lead to an increase in dimensional error. The radial depth of cut and the feed per tooth have similar effects on the dimension error. When the radial depth of cut reaches 50 μm and the feed per tooth reaches 3.5 μm/tooth, severe chip bending may produce a lot of heat. Then the temperature rise can lead to a thermal softening effect on the workpiece material. Therefore, the micro-milling force may decrease, so do the deflection and dimension errors. And a combination of machining parameters for minimum dimension error can be obtained as $n=25000 \text{ r/min}, a_p=100 \mu \text{m}, a_e=20 \mu \text{m}$ and $f=0.5 \mu \text{m/tooth}$.

3.4 Range analysis of optimization objectives

The significant contributions of the effects of machining parameters on the optimization objectives can be evaluated by range analysis value. Larger range values promise a more significant effect. And it can be calculated by Eq. (4).

$$R_j = \max(k_{1}, k_{2}, k_{3}, k_{4}) - \min(k_{1}, k_{2}, k_{3}, k_{4})$$  \hspace{1cm} (4)

Where $k_i$ is the mean value of the $i$-th level of factor $k$, $i = 1, 2, 3, 4$. $R_j$ is the range value of the $j$-th factor. Table 3 shows that the significance of machining parameters is $R_{fz} > R_n > R_{ap} > R_{ae}$ for $S_a$, $S_q$, and $D_e$. But for $D_e$, there is $R_{fz} > R_{ae} > R_{ap} > R_n$. The effects of the parameters are different from results in previous studies [25,26].

| $R_j$ | $n$   | $a_p$  | $a_e$  | $f_z$  |
|------|------|-------|-------|-------|
| $S_a$| 0.3556| 0.3221| 0.2596| 0.3918|
| $S_q$| 0.4734| 0.4422| 0.3464| 0.4958|
| $D_s$| 0.048 | 0.025 | 0.016 | 0.065 |
| $D_e$| 2.650 | 3.075 | 3.275 | 4.550 |
3.5 Multiple regression analysis

Polynomial regression has the advantages of simplicity, intuition, and low computational cost among many linear regression methods. Therefore, we choose the polynomial regression method to perform the regression analysis for the four optimization objectives. Meanwhile, a comparison is made between the quadratic fitting model using stepwise regression analysis and the model considering all the quadratic terms. The fitting performance of the model is evaluated by the significance of $p$ value, adjusting coefficient of determination $R^2$ (adj), and Bayesian Information Criterion (BIC). The comparison results are shown in Fig. 11. For $S_a$, $S_q$, and $D_e$, the stepwise regression model has a smaller $p$ value, i.e., better significance, and a smaller BIC value, i.e., avoiding overfitting. For $D_s$, the regression model with all quadratic terms has a larger $R^2$(adj), but the $R^2$(adj) of the stepwise regression model is also more than 90%.

![Fig. 11 Significance, adjusting $R^2$ and BIC criterion of regressions](image)

From the analysis above, the complexity of the regression model does not guarantee good fitting performance. Therefore, the stepwise regression method is used in our work. The regression models are Eqs. (5)-(8):

```
Direct Regression

Stepwise Regression
```

|       | $P$ | $R^2$(adj) | BIC   |
|-------|-----|------------|-------|
| Direct Regression | 0.089 | 22.74%  | 8.97  |
| Stepwise Regression | 0.602 | 59.44%  |       |

|       | $P$ | $R^2$(adj) | BIC   |
|-------|-----|------------|-------|
| Direct Regression | 0.101 | 48.08% |       |
| Stepwise Regression | 0.639 | 80.25% |       |

|       | $P$ | $R^2$(adj) | BIC   |
|-------|-----|------------|-------|
| Direct Regression | 0.007 | 92.35% | 60.7% |
| Stepwise Regression | 0.328 | 80.25% | 58.8% |

```
\[ S_a = (0.502353) - (1.37188e-4 \times A) + (0.0162087 \times B) + (0.0143241 \times C) \\
- (0.175385 \times D) + (2.769e-9 \times A^2) - (7.204e-3 \times B^2) - (0.00436369 \times C \times D) \\
+ (0.0603894 \times D^2) + (2.88859e-7 \times A \times B); \]  
\[ S_q = (1.36988) - (2.02668e-4 \times A) + (0.0205306 \times B) + (0.00441294 \times C) \\
- (0.388259 \times D) + (4.2489e-9 \times A^2) - (9.01551e-5 \times B^2) + (0.0773889 \times D^2) \\
+ (3.3833e-7 \times A \times B); \]  
\[ D_s = (1.36988) - (2.02668e-4 \times A) + (0.0205306 \times B) + (0.00441294 \times C) \\
- (0.388259 \times D) + (4.2489e-9 \times A^2) - (9.01551e-5 \times B^2) + (0.0773889 \times D^2) \\
+ (3.3833e-7 \times A \times B); \]  
\[ D_r = (-9.79754) - (0.00217969 \times A) + (0.243496 \times B) - (0.147253 \times C) \\
+ (1.56598 \times D) - (0.00078609 \times B^2) + (0.0000098493 \times A \times C) \\
- (0.0000988167 \times A \times D); \]

Fig. 12 shows the consistency evaluation between the calculation results of regression models and the experimental results. The results show that the regression models present a good predictive ability.

### 3.6 Dimension reduction analysis of optimization objectives

Fig. 13 is the correlation matrix of optimization objectives. The correlation coefficient between the dimension error \( D_e \) and the surface roughness \( S_a \) is only 0.292, and the correlation between the dimension error and other optimization objectives is also very low. Therefore, the dimension error can be considered as an independent optimization objective.

Table 4 shows the KMO and Bartlett test results of principal component analysis. The Kaiser-Meyer-Olkin measurement value is 0.564, which is greater than 0.5.
Table 4 KMO and Bartlett’s test

| Sampling adequacy | Bartlett’s test of sphericity |
|-------------------|-----------------------------|
| KMO measure       | Approximate chi-square | df | Sig. |
| 0.564             | 86.194         | 3  | 0.000 |

That means PCA analysis for $S_a$, $S_q$, and $D_s$ has a good dimension reduction effect. The $p$ value of Bartlett’s test is less than 0.01, which proves that the optimization objectives have a good linear relationship. Therefore, PCA analysis can be employed to perform dimension reduction analysis on the selected optimization objectives. Fig. 14 shows the common factor variance in PCA analysis.

Fig. 14 Common factor variance

Fig. 15 Explained total variance

Unlike the initial variation, all the explanation degree of surface characteristics variables is less than 100%. The variation of fractal dimension can be explained only by 61.4%. Fig. 15 is the total explained variance of the PCA analysis. The analysis results show that the first principal component contains the most surface characteristics variation data, accounting for 87.871% of the total accumulation. Combining with the analysis results in Fig. 16, only one principal component has an eigenvalue greater than 1. Therefore, only one principal component needs to be retained.

Fig. 16 Scree plot

Fig. 17 Component matrix

Fig. 17 details the component matrix, which represents the factor loading matrix $A$ in the PCA analysis. The transformation matrix in PCA analysis can be obtained by the principal component
loading matrix $U$ and the factor loading matrix $A$. The relationship is shown as follows:

$$U_i = A_i / \sqrt{\lambda_i}$$  \hspace{1cm} (9)

Where $\lambda_i$ is the eigenvalue. Only one principal component is extracted, so, $i=1$. According to Eq. (9), the principal component $PC_1$ is:

$$PC_1 = 0.970SA + 0.965SQ - 0.781DS$$  \hspace{1cm} (10)

Where $SA$, $SQ$, and $DS$ are the standard scores of the original optimization objectives after standardization. The relationship between the standardization process and the original optimization objective is:

$$X_m' = (X_m - \bar{X}_m) / \sigma_m$$  \hspace{1cm} (11)

Where $X_m'$ represents the $n$-th sample of the $m$-th objective after normalization, and $X_m$ represents the $n$-th sample of the $m$-th original objective. And the remaining variable formulas are:

$$\bar{X}_m = \frac{1}{p} \sum_{n=1}^{p} X_{mn}$$  \hspace{1cm} (12)

$$\sigma_m = \sqrt{\frac{1}{p} \sum_{n=1}^{p} (X_{mn} - \bar{X}_m)^2}$$  \hspace{1cm} (13)

Where $p$ is the total number of samples. The calculated mean value matrix and standard deviation matrix are:

$$\bar{X}_m = \begin{bmatrix} 0.4186 \\ 0.5418 \\ 2.4328 \end{bmatrix}$$  \hspace{1cm} (14)

$$\sigma_m = \begin{bmatrix} 0.2891 \\ 0.385 \\ 0.0358 \end{bmatrix}$$  \hspace{1cm} (15)

Then the principal component $PC_1$ can be expressed as:

$$PC_1 = 4.108S_a + 3.2975S_q + 29.6657D_s^{-1} - 16.8614$$  \hspace{1cm} (16)

### 3.7 Multi-objective optimization results

In the calculation, multi-objective optimization for the smallest roughness, the largest surface fractal dimension, and the smallest dimension error is carried out. According to the constructed constraint equation and the value range of each machining parameter, the optimal combinations of machining parameters can be obtained. On the basis of the analysis in section 3.6, optimization objective functions after dimension reduction can be expressed as:
The decision variable is \( X = [n \; a_p \; a_c \; f_z]^T \). And the range of their constraints is \( 20 \mu m \leq a_c \leq 50 \mu m, \) \( 50 \mu m \leq a_p \leq 150 \mu m, \) \( 15000 \mu m \leq n \leq 30000 \mu m, \) \( 0.5 \mu m/tooth \leq f_z \leq 3.5 \mu m/tooth. \)

NSGA-II is employed for the optimization of machining parameters. The initial population number is set as 500, and the evolutionary generation is 1500. The Pareto front and the Pareto optimal solution set are obtained, as shown in Fig. 18.

A function evaluating the membership degree is proposed for the selection of machining parameters in the Pareto solution set, as shown in Eq. (18).

\[
\max_{\max_{i}} \\min_{\min_{i}} f_{i} = \frac{f_{i} - f_{i}}{f_{i} - f_{i}^{\min}} \tag{18}
\]

Where \( f_{i}^{\max} \) and \( f_{i}^{\min} \) are the maximum and minimum value of the \( i \)-th objective function, respectively, and \( f_{i} \) is the value of the \( i \)-th objective function.

The standardized satisfaction degree of each solution in the Pareto optimal solution set can be obtained from Eq. (19).

\[
P_{j} = \frac{1}{N} \sum_{i=1}^{N} p_{i} \tag{19}
\]

The parameters with the top two largest \( P \) values in the Pareto optimal solution set are selected.

\[
X_{1} = [27880,115,50,0.525] \\
X_{2} = [24230,131,50,1.180] \tag{20}
\]

3.8 Optimization results verification

In order to verify the effectiveness of the solutions obtained in the multi-objective optimization,
comparison experiments are carried out. The optimal combinations of machining parameters and the combinations of machining parameters for the best surface quality and minimum dimension error in previous single factor experiments are also selected for the comparison. The levels of machining parameters are shown in Table 5, in which Case 1 and Case 2 are the optimal results and Case 3 and Case 4 indicate the parameters obtained in single factor experiments.

**Table 5 Machining parameters of the validation experiments**

| Symbol | Case 1 | Case 2 | Case 3 | Case 4 |
|--------|--------|--------|--------|--------|
| A      | 27880  | 24230  | 20000  | 25000  |
| B      | 115    | 131    | 60     | 100    |
| C      | 50     | 50     | 20     | 50     |
| D      | 0.525  | 1.18   | 0.5    | 0.5    |

The actual size of the workpiece is measured by the coaxial image instrument and 3-D topography is measured by the white light interferometer after conducting experiments. The results are shown in Fig. 19 and Fig. 20, respectively.

**Fig. 19 Dimensions of the thin-walled micro parts**

**Fig. 20 Surface topographies of the thin-walled micro parts**
Table 6 lists the results of validation experiments. The surface roughness and surface fractal dimension of Case 2 are only inferior to the results of Case 3, and the dimension error of Case 2 is only inferior to the results of Case 4. So, the rationality and effectiveness of the proposed machining parameters optimization method are proved by the results of the validation experiment.

| Symbol | Case 1 | Case 2 | Case 3 | Case 4 |
|--------|--------|--------|--------|--------|
|        | Optimal | Optimal | \(S_d(S_q)\)Min./\(D_s\) Max. | \(D_e\) Min. |
| \(S_a\) | 0.117 | 0.113 | 0.106 | 0.226 |
| \(S_q\) | 0.192 | 0.141 | 0.136 | 0.283 |
| \(D_s\) | 2.4886 | 2.5032 | 2.5086 | 2.4406 |
| \(D_e\) | 3.7 | 2.8 | 5.2 | 0.8 |

4. Conclusions

This paper provides a strategy for the determination of optimal parameters in micro-milling thin-walled microscale parts using PCA-based NSGA-II. The dimension error \(D_e\), the arithmetic average height \(S_a\), the root mean square height \(S_q\), and the surface fractal dimension \(D_s\) are considered as optimization objectives simultaneously. The combinations of optimal machining parameters can be acquired by this method. Finally, the optimized machining parameters are verified by micro-milling experiments.

(1) The significance contributions of machining parameters for \(S_a\), \(S_q\), and \(D_s\) are \(R_fz > R_n > R_{ap} > R_{ae}\) by order and the significance contributions for \(D_e\) are \(R_fz > R_{ae} > R_{ap} > R_n\) by order.

(2) The surface fractal dimension \(D_s\) and the arithmetic average height \(S_a\) show a negative correlation. And \(D_s\) is more sensitive to surface defects than \(S_a\), according to the results of orthogonal experiments.

(3) Regression models of stepwise regression analysis have a good performance on fitting \(S_a\), \(S_q\), \(D_s\), and \(D_e\) for its better significance, smaller BIC values, and bigger adjusting coefficient of determination compared with regression models with all the quadratic terms.

(4) The verification experiment results prove that the proposed method is effective, which can obtain optimal parameters for high surface quality as well as dimension accuracy in the micro-milling of thin-walled microscale parts.
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Declarations

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