Multi-objective parametric optimization for high surface quality and process efficiency in micro-grinding

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Abstract
In this study, for the selection of maximum material removal rate and minimum surface roughness ($R_a$) in micro-grinding of aluminum alloy through multi-response optimization, two optimization approaches are proposed based on statistical analysis and genetic algorithm. The statistical analysis–based approach applies response surface methodology according to the analysis of variance to propose a mathematical model for $R_a$. In addition, the individual desirability of material removal rate, $R_a$, and the global desirability function are calculated, and the inverse analysis is conducted to locate input setting giving maximum desirability function. The genetic algorithm–based approach uses the improved multi-objective particle swarm optimization with the experimental data trained by support vector machine. To demonstrate that the material microstructure is a significant parameter for material removal rate and $R_a$, the models with and without Taylor factor consideration are developed and compared. The optimized results achieved from both response surface methodology and improved multi-objective particle swarm optimization demonstrate that the consideration of Taylor factor can significantly improve the optimization process to achieve the maximum material removal rate and minimum $R_a$.

Keywords
Micro-grinding, surface roughness, material removal rate, response surface methodology, multi-objective particle swarm optimization, Taylor factor

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Introduction
Micro-grinding is a competitive finish machining method for better surface integrity including more compressive surface residual stress, decreased surface roughness, and smaller dimensional tolerance. Among these quality attributes, surface roughness is significant for micro-grinding and is normally represented by the arithmetic mean value, $R_a$.

The understanding of surface forming mechanism and the parameters related to the surface roughness are important. Hecker and Liang¹ proposed an analytical model to predict the arithmetic surface roughness based on a probabilistic chip thickness model considering wheel topography, process parameters, and material microstructure. For micro-machining, some factors ignored in macro-machining, such as material microstructure, cutting edge radius, and elastic recovery, became significant due to small depth of cut being comparable to the material grain size. In micro-milling process, a comprehensive floor surface roughness model was proposed to predict the surface roughness of the grooves.² The influence factors such as the relative vibration, the elastic recovery, and the minimum cutting thickness were considered in the model. However, for the surface roughness generated by micro-grinding, the mechanism is still unclear, and the analytical model has not been proposed.

Numerous investigations are conducted to optimize process parameters for minimum surface roughness. The surface roughness of flexible joint made of maraging steel 3J33 after precision milling was investigated and measured.³ In the investigation, Taguchi approach was used to design the milling experiments with the
input parameters as milling speed, feed per tooth, and axis depth of cut. In addition, analysis of variance (ANOVA) was applied to select cutting parameters for optimal surface roughness. The result shows that milling speed is the most significant factor for the surface roughness among the milling parameters. Lu et al. investigated the response surface methodology (RSM) to develop an empirical model to predict the surface roughness in micro-milling of Inconel 718. In addition, the process parameters were analyzed by ANOVA, and the minimum surface roughness was achieved by determining the optimal process parameters using genetic algorithm (GA). However, for micro-grinding, the optimization for minimum surface roughness has not been investigated.

Besides surface roughness, machining efficiency is also critical for micro-machining. In order to have high efficiency in addition to good surface finish, it is imperative to optimize the grinding conditions to minimize the surface roughness and maximize material removal rate (MRR) simultaneously. Wu et al. investigated the ductility-oriented removal mode in grinding of brittle materials. The result shows that the increase in surface speed causes higher MRR and smaller surface roughness. The MRR depends on depth of cut and workpiece speed in the model. Sunder and Yadava modeled and optimized the process parameters for higher MRR and better surface finish in surface-electrical discharge diamond grinding process. In the investigation, MRR is a function of the initial weight of workpiece, the final weight of workpiece, and the machining time. Lu et al. investigated the optimization of cutting parameters, including spindle speed, feed per tooth, and the depth of cut, for the maximum MRR and minimum surface roughness without cutter breakage in micro-milling. The Taguchi approach and regression analysis were applied to build a statistical model of surface roughness, and GA toolkit was used for optimization. Zerri et al. investigated the optimization for four objectives in turning operations. First, the experiments were designed using Taguchi method with the input parameters of cutting speed, the depth of cut, and feed rate. Then, the ANOVA and Pareto chart analysis were carried out to quantify the parameters on the output parameters. The mathematical models of the output parameters were built based on RSM and artificial neural network (ANN) approaches, and the two methods were compared. Finally, the desirability function (DF) was proposed to optimize the input parameters to lower surface roughness, increase MRR, and reduce cutting force as well as power. However, few investigations were conducted about the optimization of process parameters for maximum MRR under the constraint of surface roughness in micro-grinding process.

The previous researches reported that the forces and roughness were varied when the cutting orientation changed in the micro-machining of the single crystals. Ueda et al. experimentally investigated the variation of the pattern of chip formation and the force with the change in crystallography orientation of single crystals in cutting. Through experiments, Hansen et al. found two dislocation patterns induced by different grain orientations under deformation and applied the microstructural evolution, correlated with the grain orientation, in the model of the anisotropy of facial center cubic (FCC) metal. Zhao et al. proposed the Taylor factor to estimate the effect of crystallographic orientation (CO) on the grinding force and temperature in micro-grinding.

In this research, the optimization models with and without considering Taylor factor of material as input parameter are developed for MRR and surface roughness in micro-grinding alloy aluminum 7075 (AA7075). The micro-grinding experiments are designed following Taguchi approach. As the first optimization approach, RSM is applied to build the mathematical models, one of which is a function of surface speed, feed rate, the depth of cut, and Taylor factor for surface roughness; the other model uses the same parameters but without Taylor factor. The individual desirability for MRR and surface roughness as well as the DF are calculated. In addition, the inverse analysis is conducted, and the optimal input setting is obtained. As the second optimization approach, the improved multi-objective particle swarm optimization (IMOPSO) is used to select the input parameters for the high MRR and low surface roughness. Finally, the optimal results from both two approaches indicate that the models considering the Taylor factor improve the optimization process.

Methodology

RSM

RSM is an empirical modeling approach to determine the relationship between the input parameters and the output parameters based on experiment data. This method is applicable for nonlinear problems even when the mechanism of the process is unclear. The developed empirical model is used for predication, and then the best response is obtained by selecting the desired outputs. Moreover, the optimal input parameters are found through inverse calculation. In addition, the multi-response optimization is conducted based on RSM by developing DF and predicting the response under given input parameters. Therefore, RSM is widely used in the field for complex material cutting process.

In this paper, the depth of cut \(d_p\), the surface speed \(v_s\), the feed rate \(v_n\), and the Taylor factor \(M\) are selected for investigation. The relationship between surface roughness \(R_s\) and selected cutting parameters is expressed as

\[ R_s = C \cdot d_p^a \cdot v_s^b \cdot v_n^c \cdot M^d \]  \hspace{1cm} (1)

where \(C\) is a constant, and \(a, b, c, d\) are exponents.
To convert the nonlinear model to a linear model, logarithmic transformation is used
\[
\ln R_a = \ln C + a \ln a_p + b \ln v_r + c \ln v_w + d \ln M \quad (2)
\]
For model simplification, equation (2) can be given as follows
\[
y = \beta_0 + \beta_1 A + \beta_2 B + \beta_3 C + \beta_4 D + \delta \quad (3)
\]
where \( y \) is logarithmic transformations of the measured surface roughness, and \( A, B, C, \) and \( D \) are surface speed, feed rate, depth of cut, and Taylor factor on a logarithmic scale, respectively. The values of \( \beta \) are estimates of corresponding parameters, and \( \delta \) is the randomly distributed error term.

The quadratic response model can be represented as follows
\[
y = \beta_0 + \beta_1 A + \beta_2 B + \beta_3 C + \beta_4 D \\
+ \beta_{12} AB + \beta_{13} AC + \beta_{14} AD + \beta_{23} BC \\
+ \beta_{24} BD + \beta_{34} CD + \beta_{11} A^2 + \beta_{22} B^2 \\
+ \beta_{33} C^2 + \beta_{44} D^2 \quad (4)
\]
where \( \beta_0, \beta_1, \beta_2, \beta_3 \), and so on are coefficients to be estimated by the least squares method.

### Multi-objective particle swarm optimization

Particle swarm optimization (PSO) algorithm is an important optimization tool and used in various fields. It is a population-based search method that exploits the concept of social sharing of information following the intelligence of the socio-biological group of organisms. In general PSO, the initial population and velocity of particles are randomly generated. Each particle is denoted and its velocity as well as position in each iteration is updated, and the fitness value is evaluated. The \( P_{best} \) and \( b_{best} \) for the particles would be then updated.\(^{13} \) In general, the neutral network is usually used to train the measured data before the PSO optimization. In addition, multi-objective PSO could be conducted based on two trained data nets.

### Experiments setup and procedure

#### Materials

Aluminum alloy 7075T6 (AA7075T6) has a high strength-to-density ratio and is widely used in aerospace components. This investigation is about micro-grinding of commercial AA7075T6, with the chemical composition listed in Table 1 in weight percent.

#### Analysis and optimization

### Experimental setup and measurement condition

A CNC microscale machine tool was used for the micro-grinding experiments. Figure 1(a) shows the machine including frame, spindle, micro-grinding wheel, positioning stage, and inspection. Figure 1(b) shows the workpiece clamped. Figure 1(c) shows the magnified morphology of the Cubic boron nitride (CBN) grinding wheel 85412-BM surface. Figure 1(d) shows the relative location of the workpiece and tool. The micro-grinding experiments were designed according to Taguchi method, with surface speed, feed rate, depth of cut, and the Taylor factor as the input parameters. Four levels for each factor are shown in Table 2.

After the micro-grinding experiments, the workpieces were cleaned with acetone in an ultrasonic bath for 20 min. Then, the Bruker Nano Surface white light interferometer was utilized to measure the surface roughness \( (R_a) \) as shown in Figure 2(a). Both two-dimensional (2D) and three-dimensional (3D) surface roughness can be measured through this equipment with high precision in a sub-nano resolution. The measured area was enlarged as shown in Figure 2(b). The software system was used to process the raw data by correcting the measured curved surface to plane for exact value. Figure 2(c) shows the surface topology of one measured workpiece. In Figure 2(c), the ground surface is mainly featured by irregular caves.

The measured surface roughness after micro-grinding is collected in Table 3. In addition, the MRR during micro-grinding is calculated by equation (5) and also listed in Table 3.

\[
MRR = a_p \bullet v_w \quad (5)
\]

The orthogonal-designed micro-grinding experiments were conducted with the variation of the surface speed, feed rate, depth of cut, and the Taylor factor. The factors are arranged according to the orthogonal matrix \( L_{16} \).
Similarly, $S_B, S_C, S_D$, and $S_E$ are calculated. The contribution ratio for each factor is calculated as the percentage of summation of squares of differences. For $R_a$, RSM is also utilized to obtain the ANOVA table as shown in Table 4, where estimate is the input factor, $S_E$ is the results by formal (6), t-Start is $R_a$ factor, $p$ value reflected the significance of each term, and intercept is the test code.

From the ANOVA table, the influence of the input parameter could be established if the “$p$ value” is less than 0.05. It could be found that the surface speed, feed rate, the depth of cut, and Taylor factor are significant for $R_a$. Figure 3 represents the surface response plots of $R_a$ versus different significant variables. The curvatures of plots indicate the interaction between variables.

$$s_A = \frac{1}{n} \sum_{j=1}^{n} \left( A_j - \frac{1}{n} \sum_{j=1}^{n} A_j \right)^2$$  \hspace{1cm} (6)
is obtained as follows

In addition, the Taylor factor is significant to the variance and the depth of cut, while increasing the surface speed. Roughness can be obtained by decreasing the feed rate.

ANOVA: analysis of variance.

Table 3. Layout of \( L_{16} \) orthogonal arrays.

| Case number | Micro-grinding conditions | Response factors |
|-------------|----------------------------|------------------|
|             | \( V_s \) (mm/s) | \( V_w \) (mm/min) | \( a_p \) (\( \mu \)m) | \( M \) | \( R_a \) (\( \mu \)m) | MRR (\( \mu \)mm²/s) |
| 1           | 1.57                      | 1                | 1               | 5.60 | 0.397 | 0.017 |
| 2           | 1.57                      | 5                | 10              | 8.44 | 1.043 | 0.833 |
| 3           | 1.57                      | 10               | 20              | 9.11 | 1.501 | 3.333 |
| 4           | 1.57                      | 20               | 30              | 9.75 | 2.053 | 10.000 |
| 5           | 3.14                      | 1                | 10              | 8.44 | 0.466 | 0.167 |
| 6           | 3.14                      | 5                | 1               | 9.75 | 0.547 | 0.083 |
| 7           | 3.14                      | 10               | 30              | 9.11 | 1.264 | 5.000 |
| 8           | 3.14                      | 20               | 20              | 5.60 | 1.501 | 6.667 |
| 9           | 6.28                      | 1                | 20              | 9.75 | 0.266 | 0.333 |
| 10          | 6.28                      | 5                | 30              | 8.44 | 0.779 | 2.500 |
| 11          | 6.28                      | 10               | 1               | 9.11 | 0.547 | 0.167 |
| 12          | 6.28                      | 20               | 10              | 5.60 | 1.043 | 3.333 |
| 13          | 9.42                      | 1                | 30              | 9.11 | 0.410 | 0.050 |
| 14          | 9.42                      | 5                | 20              | 9.75 | 0.671 | 1.667 |
| 15          | 9.42                      | 10               | 10              | 9.75 | 0.757 | 1.667 |
| 16          | 9.42                      | 20               | 1               | 8.44 | 0.382 | 0.333 |

MRR: material removal rate.

Table 4. ANOVA table for \( R_a \).

| Estimated coefficients | Estimate | SE | t-Stat | p value |
|------------------------|----------|----|--------|---------|
| Intercept              | -1.485   | 2.483 | -0.598 | 0.586 |
| A                      | 9443.425 | 0.296 | 3.186  | 0.019  |
| B                      | 1281.113 | 0.591 | 2.171  | 0.036  |
| C                      | -2683.277| 0.277 | -9.671 | 0.041  |
| D                      | 3584.986 | 5.303 | 0.676  | 0.022  |
| AB                     | -0.857   | 0.127 | -6.771 | 0.093  |
| AC                     | 0.081    | 0.193 | 0.422  | 0.746  |
| AD                     | 0.251    | 0.265 | 0.948  | 0.517  |
| BC                     | 0.088    | 0.217 | 0.404  | 0.756  |
| BD                     | 0.960    | 0.875 | 1.097  | 0.471  |
| CD                     | 0.778    | 0.237 | 3.280  | 0.188  |
| A^2                    | -0.700   | 0.324 | -2.165 | 0.275  |
| B^2                    | -0.132   | 0.067 | -1.982 | 0.298  |
| C^2                    | -0.325   | 0.074 | -4.386 | 0.143  |
| D^2                    | -3.203   | 2.689 | -1.191 | 0.445  |

ANOVA: analysis of variance.

From the plot, it could be seen that the better surface roughness can be obtained by decreasing the feed rate and the depth of cut, while increasing the surface speed. In addition, the Taylor factor is significant to the variance of surface roughness.

According to the ANOVA table, a quadratic model is obtained as follows

\[
\log_{10} R_a = -1.485 - 9443.425A + 1281.113B
- 2683.277C + 3584.986D
- 0.857AB + 0.081AC + 0.251AD
+ 0.088BC + 0.96BD
+ 0.778CD - 0.7A^2 - 0.132^2B^2
- 0.325C^2 - 3.203D^2
\]

For the multi-response optimization, each individual response is converted into their corresponding desirability \( d_i \) to get the global DF given by

\[
D = [d_1^s \times d_2^s \times \ldots \times d_n^s]^{\frac{1}{n}} = \prod_{i=1}^{n} (d_i^s)^{\frac{1}{n}} \tag{8}
\]

where \( r_i \) is the relative importance of individual response to the process, and \( d_i \) is given as follows

For maximization:
\[
d_i = \begin{cases} 
0 & \text{if } y < y_{\text{min}} \\
\left(\frac{y-y_{\text{min}}}{y_{\text{max}}-y_{\text{min}}}\right)^{w_i} & \text{if } y_{\text{min}} \leq y \leq y_{\text{max}} \\
1 & \text{if } y > y_{\text{max}}
\end{cases} \tag{9}
\]

For minimization:
\[
d_i = \begin{cases} 
1 & \text{if } y < y_{\text{min}} \\
\left(\frac{y-y_{\text{min}}}{y_{\text{max}}-y_{\text{min}}}\right)^{w_i} & \text{if } y_{\text{min}} \leq y \leq y_{\text{max}} \\
0 & \text{if } y > y_{\text{max}}
\end{cases} \tag{10}
\]

where \( w_i \) is the weight of the response which is fixed as 1.

The DF and the relative importance of MRR and \( R_a \) are listed in Table 5.

Then, the global DF becomes

\[
\text{DF} = [d_1^s \times d_2^s]^{\frac{1}{s}} \tag{11}
\]

The objective is to maximize DF by choosing the optimal parameter combination. Based on the mathematical model for \( R_a \) and MRR, the predicted results for single-factor experiments, the DFs, and the maximum DF are calculated. The input parameter ranges are as follows: 1.57 mm/s \( \leq V_s \leq 9.42 \) mm/s, 1 mm/min \( \leq V_w \leq 20 \) mm/min, 1 \( \mu \)m \( \leq a_p \leq 30 \) \( \mu \)m, and 5.60 \( \leq M \leq 9.75 \). The interval is 0.1 mm/s for \( V_s \), 1 mm/min for \( V_w \), 1 \( \mu \)m for \( a_p \), and 1 for \( M \).
Similarly, the mathematical models of $R_a$ and MRR without considering Taylor factor can be obtained using RSM approach, and then the optimal setting of parameters can be achieved for maximum MRR and minimum $R_a$. To demonstrate the significance of Taylor factor to $R_a$ and MRR, the optimal results predicted from the two models are compared and shown in Table 6. The model obtained from RSM approach considering Taylor factor is named Model 1, and the one without considering Taylor factor is named Model 2.

The comparison results show that the optimal result of $R_a$ predicted from Model 1 is less than that from Model 2, but the optimal result of MRR from the two models is the same. It can be concluded that Model 1 improves the optimization process with the consideration of Taylor factor.

### Table 5. The desirability function and the relative importance.

| Response | Optimization objective | Desirability function ($d_i$) | Relative importance |
|----------|------------------------|-------------------------------|--------------------|
| MRR      | maximization           | $d_i = \frac{MRR_{max} - MRR}{MRR_{max} - MRR_{min}}$ | 3                  |
| $R_a$    | minimization           | $d_i = \frac{R_a_{max} - R_a_{min}}{R_a}$ | 4                  |

MRR: material removal rate.

### Table 6. Comparison between the predicted optimal results of the two models.

| Model type | Process parameters | Response values |
|------------|--------------------|-----------------|
|            | $V_s$ (mm/s) | $V_w$ (mm/min) | $a_p$ ($\mu$m) | $M$ | $R_a$ ($\mu$m) | MRR ($\mu$m$^2$/s) |
| Model 1    | 8.57             | 16              | 26              | 5.6 | 0.5837         | 6933.333             |
| Model 2    | 8.57             | 16              | 26              | –   | 0.9449         | 6933.333             |

MRR: material removal rate.

**The optical result from IMOPSO**

Support vector machine (SVM)\(^{16}\) is used to train the measured data in the multi-classification problems with small samples and nonlinear characteristics, and the classification effect of SVM will be more accurate when combined with IMOPSO.

For MRR and $R_a$, the trained result is compared to the measured data, which is shown in Figure 4.

Then, the trained nets are used to predict the MRR and $R_a$ produced in micro-grinding and conduct the inverse analysis. Finally, the optimal process parameters as well as the optimal MRR and $R_a$ are obtained by IMOPSO, with $W_{max}$ and $W_{min}$ taken as 0.9 and 0.4, respectively. The initial swarm size is set at 80 with maximum iteration of 150. The constants $C1$ and $C2$
are taken as 1 with initial inertia weight of 0.8. The iteration is carried out, and the predicted output is obtained.

Similarly, the optimization model of $R_a$ and MRR without considering Taylor factor can also be obtained by combining SVM and IMOPSO. The optimal setting of parameters is selected under maximum MRR and minimum $R_a$. To demonstrate the significance of Taylor factor to $R_a$ and MRR, the optimization models with and without considering Taylor factor are developed through the RSM and IMOPSO approaches, respectively.

The comparison results show that the optimal $R_a$ predicted from Model 3 is less than that from Model 4, and the optimal MRR predicted from Model 3 is larger than that from Model 4. It can be concluded that Model 3 improves the optimization process by considering Taylor factor.

### Conclusion

To obtain the high quality of the machined surface and high efficiency in micro-grinding, the multi-response parametric optimizations are conducted in this investigation. The input parameters including surface speed, feed rate, the depth of cut, and Taylor factor are considered as the influence factors. The output responses are surface roughness ($R_a$) and MRR. The Taguchi-designed experiments are conducted with four factors and four levels. Based on the experiment data, two optimization approaches are utilized in this investigation.

To demonstrate the significance of Taylor factor to $R_a$ and MRR, the optimization models with and without considering Taylor factor are developed through the RSM and IMOPSO approaches, respectively. By comparing the optimal results predicted from the models developed by RSM approach, it indicates that the optimal $R_a$ is smaller when the model considers Taylor factor, while the optimal MRR remains the same. Therefore, the consideration of Taylor factor will improve the optimization developed under RSM. By comparing the optimal results predicted from the models developed by IMOPSO approach, it indicates that the optimal $R_a$ becomes smaller and the optimal MRR is larger when Taylor factor is taken into consideration.

In conclusion, the comparisons demonstrate that the Taylor factor has a significant effect on $R_a$ and MRR.

In addition, the mathematical model developed by RSM inclines to reach maximum MRR and minimum surface roughness simultaneously. However, the model developed by IMOPSO finds optimal parameters that lower MRR and lower surface roughness. For the lower $R_a$ and higher MRR simultaneously, in the input parameter ranges, the optimal combination of process parameters from the RSM approach is $V_s = 8.57 \text{ mm/s}, V_w = 16 \text{ mm/min}, a_p = 26 \mu\text{m}$, and $M = 5.6$ for $R_a = 0.5837 \mu\text{m}$ and MRR = 6933.33.
μm$^2$/s; the optical combination of process parameters from the IMOPSO approach is $V_s = 7.2886$ mm/s, $V_v = 1.2979$ mm/min, $d_p = 15.2776$ μm, and $M = 8.8772$ for $R_a = 0.6042$ μm and MRR = 863.4970μm$^2$/s. In conclusion, RSM inclines to optimize the process parameters to obtain the maximum MRR with the surface roughness not better; IMOPSO inclines to optimize the process parameters to obtain better surface and MRR simultaneously. So, comprehensive evaluation IMOPSO is better than RSM.

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References
1. Hecker RL and Liang SY. Predictive modeling of surface roughness in grinding. Int J Mach Tool Manu 2003; 43(8): 755–761.
2. Lu X, Zhang H, Jia Z, et al. Floor surface roughness model considering tool vibration in the process of micro-milling. Int J Adv Manuf Tech 2017; 94(9–12): 4415–4425.
3. Yao Y, Zhu HT, Huang CZ, et al. Surface roughness and topography analysis in precision milling of 3133 maraging steel. Mater Sci Forum 2016; 874: 497–502.
4. Lu X, Wang F, Wang X, et al. Modelling and optimisation of cutting parameters on surface roughness in micro-milling Inconel 718 using response surface methodology and genetic algorithm. Int J Nanomanuf 2018; 14(1): 34–50.
5. Wu C, Guo W, Wu Z, et al. Ductility-oriented high-speed grinding of silicon carbide and process design for quality and damage control with higher efficiency. Int J Adv Manuf Tech 2019; 105(7–8): 2771–2784.
6. Sunder S and Yadava V. Modelling and optimisation of material removal rate and surface roughness in surface-electrical discharge diamond grinding process. Int J Ind Syst Eng 2014; 17(2): 133–151.
7. Lu X, Zhang H, Jia Z, et al. Cutting parameters optimization for MRR under the constraints of surface roughness and cutter breakage in micro-milling process. J Mech Sci Technol 2018; 32(7): 3379–3388.
8. Zerti A, Yallese MA, Meddour I, et al. Modeling and multi-objective optimization for minimizing surface roughness, cutting force, and power, and maximizing productivity for tempered stainless steel AISI 420 in turning operations. Int J Adv Manuf Tech 2019; 102(1–4): 135–157.
9. Ueda K, Iwata K and Nakayama K. Chip formation mechanism in single crystal cutting of β-brass. CIRP Ann 1980; 29(1): 41–46.
10. Hansen N, Huang X and Winther G. Grain orientation, deformation microstructure and flow stress. Mat Sci Eng A 2008; 494(1–2): 61–67.
11. Zhao M, Ji X and Liang SY. Micro-grinding temperature prediction considering the effects of crystallographic orientation and the strain induced by phase transformation. Int J Precis Eng Man 2019; 20, 1861–1876.
12. Zhao M, Ji X and Liang SY. Force prediction in micro-grinding maraging steel 3J33b considering the crystallographic orientation and phase transformation. Int J Adv Manuf Tech 2019; 103(5–8): 2821–2836.
13. Mohanty S, Mishra A, Nanda BK, et al. Multi-objective parametric optimization of nano powder mixed electrical discharge machining of AlSiCp using response surface methodology and particle swarm optimization. Alex Eng J 2018; 57(2): 609–619.
14. Quan GZ, Mao YP, Li GS, et al. A characterization for the dynamic recrystallization kinetics of as-extruded 7075 aluminum alloy based on true stress–strain curves. Comp Mater Sci 2012; 55: 65–72.
15. Zhao M, Ji X and Liang SY. Influence of AA7075 crystallographic orientation on micro-grinding force. Proc IMechE Part B: J Engineering Manufacture 2018; 232(8): 1831–1843.
16. Ghosh G, Mandal P and Mondal SC. Modeling and optimization of surface roughness in keyway milling using ANN, genetic algorithm, and particle swarm optimization. Int J Adv Manuf Tech 2017; 100(5–8): 1223–1242.