Analysis of Cutting Performance of Tool based on Analytic Hierarchy Process and Grey-fuzzy Evaluation Method

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Analysis of cutting performance of tool based on analytic hierarchy process and grey-fuzzy evaluation method

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Abstract: Studies show that in the cutting process, different parameters have different importance to performance indicators. Accordingly, it is necessary to define the importance of different parameters to performance indicators to study the correlation between parameters and performance indicators accurately. In the present study, the side milling process of titanium alloy by the end milling cutter is considered as the research object, analytic hierarchy process and grey-fuzzy evaluation method are used to evaluate the importance of tool geometric parameters and operating parameters on tool wear rate and material removal. It is found that applying the average method to remove the parameter level, makes each parameter calculate the same result. Therefore, it should be combined with other data processing methods to resolve the above problem. Finally, the range analysis method is applied to obtain the optimal parameter level of different parameters for each performance indicator in the orthogonal table. The obtained results show that helix angle has the highest importance comprehensive evaluation value, followed by feed per tooth. For the tool wear rate and material removal amount, the optimal horizontal combination of parameters was obtained successively.

Keywords Titanium alloy, Side milling, Tool wear rate, Material removal amount, Analytic hierarchy process, Grey-fuzzy evaluation method, Range analysis method

Declarations

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We have no conflict of interest to declare.

Conflicts of interest/Competing interests

The authors declare that there is no conflict of interests regarding the publication of this article.

Availability of data and material

The datasets used or analyzed during the current study are available from the corresponding author on reasonable request.

Code availability (Not applicable)

Authors' contributions

CaiXu Yue, Daxun Yue and Xianli Liu contributed to the conception of the study; Daxun Yue carried out the research of analytic hierarchy process and grey-fuzzy evaluation method as well as the simulation and experimental verification of the accuracy of the simulation model;Ming Li contributed to the processing of finite element simulation data;Anshan Zhang,Mingxing Li and Steven Y. Liang helped perform the analysis with constructive discussions.

Ethics approval

The content studied in this article belongs to the field of metal processing, does not involve humans and

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animals. This article strictly follows the accepted principles of ethical and professional conduct.

Consent to participate

My co-authors and I would like to opt in to In Review.

Consent for publication

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1 Introduction

Titanium alloy is a typical refractory material with superior characteristics, including high corrosion resistance and high strength to weight ratio [1]. Accordingly, this alloy is widely applied in aerospace and other high-tech applications [2]. Generally, the final shape of most mechanical parts is obtained through the cutting process [3]. However, the cutting efficiency in the machining process of titanium alloy workpiece is relatively low, thereby shortening the tool life and generating manufacturing problems as well. In order to solve the above problems, it is necessary to study the correlation between different parameters and performance indicators, but there are many influencing parameters in the cutting process,the tool shape parameters include the rake angle, clearance angle and helix angle, and the operating parameters include the cutting speed, feed depth and cutting depth. Therefore, in order to simplify the calculation and speed up the research process, it is necessary to prioritize the importance of different parameters to performance indicators.

Reviewing the literature indicates that many methods, including the range analysis method and grey correlation method have been proposed so far to analyze the importance of different parameters to performance indicators. In the range analysis method, the importance degree of parameters is obtained by analyzing the performance of indicators in the orthogonal experiment. Yuan et al. [4] performed an orthogonal milling test on the down-milling device and applied the range analysis method to analyze the influence degree of spindle speed, cutting depth and feed per tooth on the burr width. Then the ranking of the influence degree of the three parameters on the burr width was obtained. Hu et al. [5] carried out orthogonal tests and used the range analysis method to analyze the importance of the cutting depth, cutting width, spindle speed and feed per tooth in the cutting force of carbide end mills. Currently, grey relational analysis (GRA) is widely applied as an optimization method to analyze uncertain correlations between various factors in a given system [6]. Li et al. [7] studied the importance of parameters in the thermal error model of machine tools through the grey correlation method and obtained critical temperatures. After optimizing the thermal error model, the searching times of variables were greatly shortened. Gao [8] used the grey correlation method to evaluate the importance of tool parameters on the surface roughness. The obtained results showed that the spindle speed has the highest impact on surface roughness, while the roll angle is the least important parameter.

The metal cutting process is a fuzzy and complex process. In addition to the interaction between different parameters, there is also an interaction between performance indicators. Therefore, the fuzzy comprehensive evaluation method has been widely applied in this field. On the other hand, the grey correlation method can be applied to solve the problem of poor information systems. Accordingly, the characteristics of these two methods can be combined to get the grey-fuzzy evaluation method, which has the best performance in the field of cutting. Rajeswari S. et al. [9] conducted an orthogonal test of milling Al/SiC and used the grey-fuzzy evaluation method to optimize the parameter level of surface roughness and tool wear. Accordingly, they obtained the best parameter level and the minimum performance indicators in the studied cases. N. Tamiloli et al. [10] studied end milling of aluminum alloy AA6082T6 with a coated milling cutter and applied the grey-fuzzy method to analyze different parameters, including the average roughness, root mean square roughness and material removal rate and obtained the optimal milling process parameters. Based on the orthogonal test of turning structural steel, C. Moganapriya1 et al. [11] combined the grey correlation and fuzzy logic to optimize different levels of parameters in the orthogonal test table and obtained the best combination of turning parameters and cutting fluid velocity with respect to the tool wear and surface roughness.

Considering the performed literature survey, the main objective of the present study is to analyze the

importance of the different parameters on the performance indicators through the range analysis method and grey correlation method. It is worth noting that since the cutting process can be considered a fuzzy process, applying only one of the two abovementioned methods cannot get accurate results. Consequently, it is necessary to apply the grey-fuzzy evaluation method to solve the problem. Although the grey-fuzzy method has been applied for the horizontal optimization of parameters in orthogonal experiments, and when scholars in the literature mentioned above used this evaluation method for research, they mainly solved the trigonometric function of membership degree through mathematical programming software such as MATLAB. However, the grey-fuzzy evaluation method in the form of grey correlation matrix instead of membership function has not been studied in the metal cutting field, and the analytic hierarchy process and grey-fuzzy evaluation method have not been combined to evaluate the comprehensive importance of parameters to multiple performance indicators in this field.

The side milling of titanium alloy by the end milling cutter is considered as the research object, the material removal amount in a period of time and the tool wear rate when machining to a certain distance are taken as the performance indicators. In the process of dealing with parameter levels, the average method leads to the same results. Therefore, it is necessary to combine the mean processing parameters with other methods to process the data and modify the evaluation method for the orthogonal test. Then the influence of different parameters on the performance indicators is analyzed. Finally, optimal levels of different parameters in the orthogonal table are obtained for each performance indicator.

2 Evaluation method of parameter importance

2.1 Assessment method of the parameter importance

The fuzzy evaluation method based on the grey relational degree (grey-fuzzy evaluation method) has the advantages of grey relational analysis and fuzzy logic method simultaneously [12]. In this method, the grey relational degree is utilized to replace the membership function and obtain the membership matrix. This judgment method is a method of judging things or phenomena with fuzzy factors in the case of insufficient information [13]. Compared with conventional evaluation methods, this method enhances the objectivity of the evaluation process [14]. However, since analyzing the importance of different parameters and multiple performance indicators should be considered, the problem of obtaining the same calculation results with different parameters appears when the input data is processed only by the mean method. Therefore, it is necessary to combine the mean value method with other data processing methods to resolve the abovementioned shortcoming. In this regard, in the present study, the dimensionless method is combined with the mean value method. Fig. 1 shows the improved parameter importance flowchart, where the matrix M_i will be discussed in section 2.3.1.

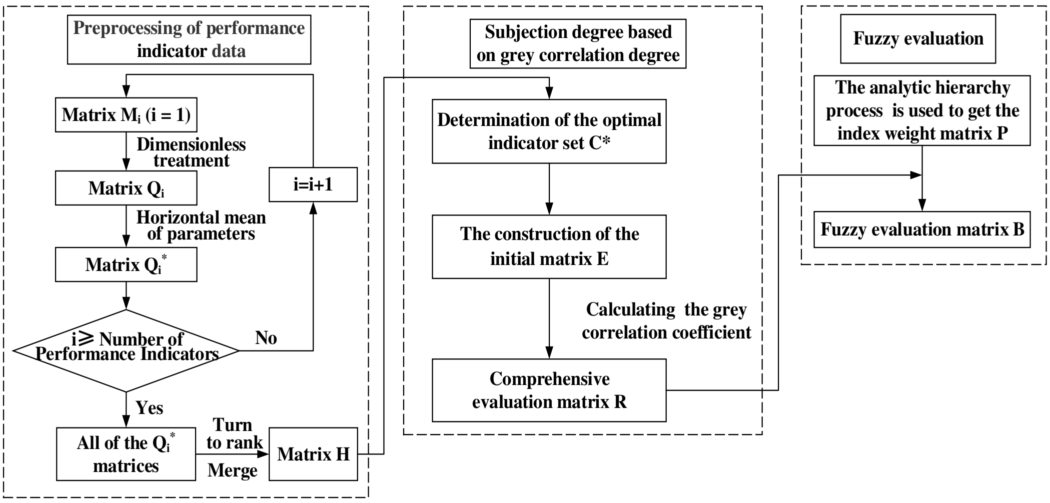


Fig 1. Improved importance evaluation flowchart

2.2 Calculation of the weight allocation based on the analytic hierarchy process

In the present study, tool wear rate and material removal amount within a certain period of time and machining to a certain distance are used as performance indicators. In order to obtain the comprehensive

importance of different parameters to the above performance indicators, it is necessary to assign weights to each indicator.

Analytic hierarchy process (AHP) is a complex decision-making analysis method that can be applied to solve multiple objectives by combining qualitative analysis with a quantitative one [15]. This method consists of four main steps, including the establishment of the ladder hierarchy structure model, construction of judgment matrices in each hierarchy, calculation of weight vectors and the consistency test, and calculation of the order of advantages and disadvantages of each scheme [16]. The grey-fuzzy evaluation method requires the weight value of performance indicators, which can be obtained according to the analytic hierarchy process through the following three steps:

(1) According to the indicator factor set, the i^{th} indicator is compared with other performance indicators, and its importance is scaled from 1 to 9 to obtain the scaling matrix $U_i=\{U_{1i},U_{2i},...,U_{mi}\}$.

(2) Calculate the weight value of the i^{th} indicator based on the scale matrix U_i, and the expression is shown in Eq. 1,

$$P_i=\left(\sum_{j=1}^{m}U_{ji}\right)^{-1},\text{j=1,2,3...,m} \qquad (1)$$

Where U_{ji} is the value obtained by comparing the j^{th} performance indicator with the i^{th} one.

(3) Calculate the weight value of the remaining (m-1) performance indicators, and the expression is shown in Eq. 2,

$$P_{ji}=P_i\cdot U_{ji},\text{j=1,2,3...,m} \qquad (2)$$

2.3 Solving the membership degree based on the grey relational degree

Assume the parameter set $A=\{A_1,A_2,...,A_n\}$, where A_j(i=1,2,...,n) is the j^{th} parameter participating in the evaluation. Moreover, assume the performance indicator set $Y=\{Y_1,Y_2,...,Y_m\}$, where Y_i(i=1,2,...,m) is the i^{th} performance indicator. For the level of parameters in the orthogonal experiment, the number of levels of different parameters is set to u.

2.3.1 Preprocessing of performance indicator data

In order to obtain orthogonal test table performance indicator value, it is necessary to calculate the first j factor and the first s level of the indicator value of the sum of the average k_{sj} and then the matrix M_i consisting of different parameters and different levels of i^{th} indicators can be established. Eq. 3 indicates that different performance indicators are pretreated in the matrix M_i. Then each performance indicator matrix is preprocessed.

$$M_i=\begin{bmatrix} k_{11} & k_{22} & \Lambda & k_{1n} \\ k_{21} & k_{22} & \Lambda & k_{2n} \\ \mathrm{M} & \mathrm{M} & \mathrm{M} & \mathrm{M} \\ k_{u1} & k_{u2} & \Lambda & k_{un} \end{bmatrix}_{u\times n} \qquad (3)$$

Since indicator factors involving in the decision have different dimensions, they cannot be directly compared with each other. Accordingly, the matrix M_i should be non-dimensionalized. Assume that the minimum and maximum values of the j^{th} parameter in the matrix M_i under a certain indicator are k_j^{min} and k_j^{max}, respectively. Then the dimensionless matrix Q_i can be obtained as Eq. 4,

$$Q_{sj}=\frac{k_{sj}-k_j^{\min}}{k_j^{\max}-k_j^{\min}} \qquad (4)$$

where s=1,2,...,u and j=1,2,...,n. Then the dimensionless values at different levels under the same factor are averaged, shows as Eq. 5,

$$Q_j^* = \frac{\sum_{s=1}^{u} Q_{sj}}{u} \qquad (5)$$

where Q_i^* denotes the averaging matrix.

2.3.2 Solving the membership degree based on the grey correlation

Matrix Q^* of all performance indicators can be obtained through the presented membership calculation in Fig. 1, where its rank is merged to obtain matrix H. Finally, the comprehensive relation matrix R can be calculated from the Eq. 6 for the grey correlation coefficient:

$$\eta(i) = \frac{\min_j \min_i \left|C_i^* - C_{ji}^*\right| + \rho \max_j \max_i \left|C_i^* - C_{ji}^*\right|}{\left|C_i^* - C_{ji}^*\right| + \rho \max_j \max_i \left|C_i^* - C_{ji}^*\right|} \qquad (6)$$

where C_i^* is the optimal value of the same performance indicator in matrix H and $\rho \in [0,1]$ is the resolution coefficient, which is normally set to $\rho=0.5$ [17].

2.4 Fuzzy judgment

Each row vector of the fuzzy relation matrix R expresses the evaluation importance of different parameters on the same performance indicator. However, due to the different statuses and roles of each indicator in the metal cutting process, the weight distribution of each performance indicator $P_i \in [0,1]$ is used instead. Then the mathematical model for the comprehensive evaluation of the importance of parameters of titanium alloy side milling with end milling cutter, shows as Eq. 7,

$$B = P \cdot R \qquad (7)$$

where matrix B is the comprehensive evaluation matrix of the importance of different parameters to multiple performance indicators. The values in the matrix express the comprehensive importance of parameters to performance indicators. The greater the value, the higher the importance degree.

3 Finite element simulation of the milling process

3.1 Establishment and verification of the finite element model of the milling process

If the orthogonal cutting test including tool parameters is carried out, it is necessary to purchase a certain number of end mills with different tool parameters. And the indicators include performance indicators related to tool wear, so the workpiece will be wasted. In order to reduce manufacturing expenses, it is intended to simulate the orthogonal test of titanium alloy side milling with an end milling cutter by DEFORM-3D software. In this regard, the maximum value of the cutting force along each direction was used as the performance indicator to simulate the milling process, and then the simulation model was verified through experiments.

3.1.1 Establishment of the simulation model

With the continuous development of numerical simulations, commercial software can better reflect the actual machining processes. In this regard, diverse processes of numerical control machine tools have been investigated using the finite element simulation, and then obtained data have been applied to study the process [18]. However, in the process of researching the cutting process simulation, different simulation software is needed according to the different performance indicators [19]. DEFORM-3D is a process simulation software based on the finite element method (FEM), which aims to analyze various forming and heat treatment processes in metal forming industries [20]. This software is robust and is easy to use [21]. Fig. 2 shows the cutting simulation flowchart of DEFORM-3D software.

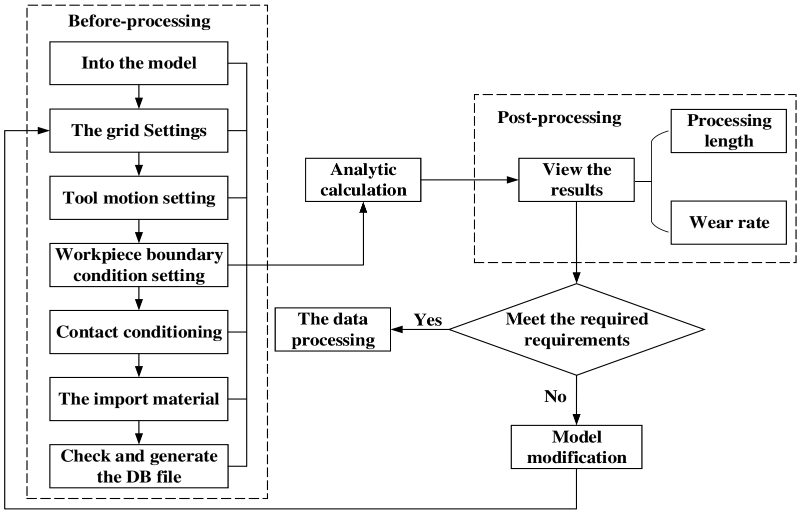
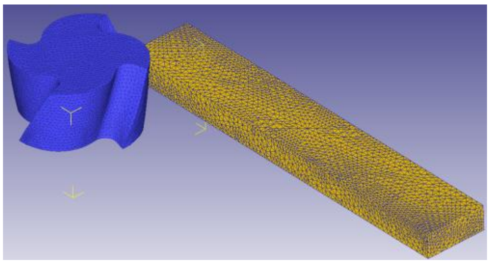


Fig. 2 Cutting simulation flowchart of DEFORM_3D software

In the present study, UG software is used for 3D modeling. Fig. 3(a) shows the 3D model of the end milling cutter, indicating that the workpiece is made of a block of titanium alloy. In order to simplify the model and accelerate the calculation speed, the model of milling cutter and the model of titanium alloy workpiece are simplified. Fig. 3(b) illustrates the simplified simulation model. It should be indicated that the workpiece thickness was modified according to different cutting depths. Table 1 shows cutting parameters in the milling test.

(a) End milling cutter model



(b) The simulation model

Fig. 3 Simulation model of the side milling process

Table 1 Settings of milling cutting parameters

Cutting speed (m/min)	Feed speed (mm/min)	Cutting depth (mm)	Cutting width (mm)
31.40	400	3	0.8
37.68	400	3	0.8
47.10	400	3	0.8

3.2.2 Material constitutive model

The constitutive model of titanium alloy during the milling can be expressed as a function of stress, strain, strain rate and temperature [22]. Reviewing the literature indicates that the J-C model has been widely applied in finite element simulation, mainly because of its few parameters and simple form [23]. Accordingly, the J-C constitutive reinforcement model was selected. The expression form of J-C constitutive model equation is shown in Eq. 8,

$$\bar{\sigma} = \left[A + B(\bar{\varepsilon})^n\right] \cdot \left[1 + C\ln\frac{\bar{\varepsilon}}{\bar{\varepsilon}_0}\right] \cdot \left[1 - \left(\frac{T - T_r}{T_m - T_r}\right)^m\right] \tag{8}$$

where σ, ε and ε_0 are equivalent flow stress, equivalent plastic strain rate and reference plastic strain rate, respectively. T, T_r and T_m denote the absolute temperature, ambient temperature and melting temperature of the workpiece material, respectively. A, B, C, m and n are the yield strength, hardening modulus, strain rate sensitivity coefficient, heat softening coefficient and strain hardening index, respectively. J-C parameters of the Ti6Al4V

constitutive model are presented in Table 2.

Table 2 J-C parameters for Ti-6Al-4V alloy

A(MPa)	B(MPa)	C	m	n	$\bar{\varepsilon}_0$ (s^{-1})	T_m(℃)	T_r(℃)
875	793	0.01	0.71	0.386	1	1560	20

3.3 Validation of the finite element model

3.3.1 Experimental setting

In the present study, a machining center (VDL-1000E, Dalian Machine Tool Group, China) was used as the experimental milling machine tool. The cutter was made of a 4-edge cemented carbide end milling cutter with a diameter of 10mm. The block titanium alloy workpiece was selected as the machining object with a size of 100mm×100mm×100mm. Moreover, cutting force signals were gathered by a rotary dynamometer (9171A, Kistler, Switzerland) and the cutting force components along x-, y- and z-directions were recorded by Dynoware signal analyzer software. Fig. 4 shows the experimental instruments and equipment used in the experiment.

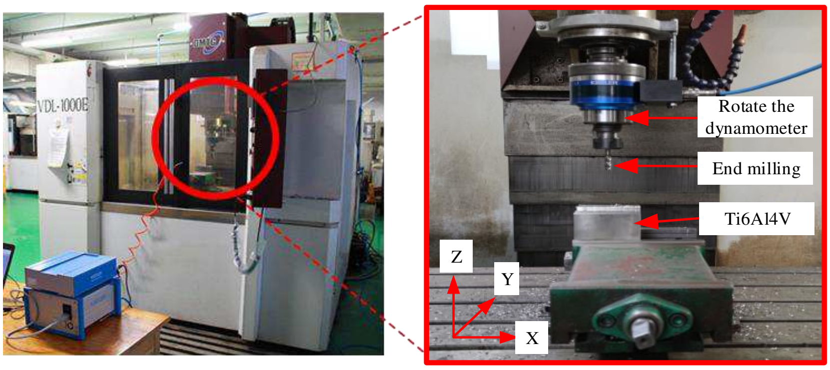


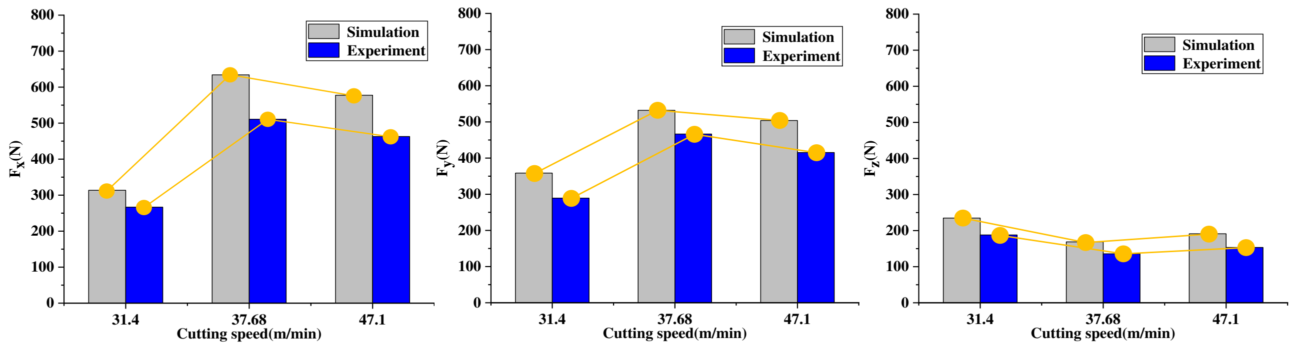
Fig. 4 Experimental instruments and equipment used in the experiment

3.3.2 Simulation and experimental results and verification

Table 3 presents the maximum cutting forces along three directions. The experimental value is selected as the cutting force value in a group. Furthermore, the simulation value is selected as the cutting force data within 5mm of machining, and unreasonable data compared to the experimental value is removed. Fig. 5 compares the simulation and experimental values of the maximum cutting forces along three directions at different cutting speeds. It is observed that the variation trend of the simulation and experimental values with the cutting speed are consistent, and the maximum and minimum errors are 24.822% and 14.036%, respectively. Accordingly, it is concluded that the simulation value is in good agreement with the experiment and the simulation model is reliable. Therefore, the finite element simulation model replaces experiments to obtain the required data.

Table 3 Obtained cutting forces for different cutting speeds

	Cutting speed(m/min)	Simulation(N)	Experiment(N)
F_x	31.40	313.613	266.791
	37.68	634.243	510.750
	47.10	577.552	462.902
F_y	31.40	358.606	289.408
	37.68	532.094	466.600
	47.10	503.908	415.483
F_z	31.40	234.752	188.069
	37.68	168.884	135.653
	47.10	191.216	153.299



(a) x-direction (b) y-direction (c) z-direction

Fig. 5 Cutting forces along different directions

3.4 Selecting simulation parameters and setting the performance index

In the previous section, it was concluded that the milling simulation model obtained from DEFORM-3D software is reliable and the numerical simulation can replace the experiment. In this section, it is intended to increase efficiency and increase the expenses of the machining. In this regard, the tool wear rate during machining a certain distance and the material removal amount within a certain time were taken as the performance indicators, and finite element simulations were performed to calculate these indicators.

3.4.1 Selection of simulation parameters

In the present study, side milling of titanium alloy Ti6Al4V with cemented carbide end mills was taken as the research object. Fig. 6 schematically shows the tools parameters. Considering the characteristics of side milling of the end mill, edge rake angle, first back angle and helix angle were selected as tool parameters. Meanwhile, cutting speed, feed per tooth, cutting depth and cutting width were considered as operating parameters.

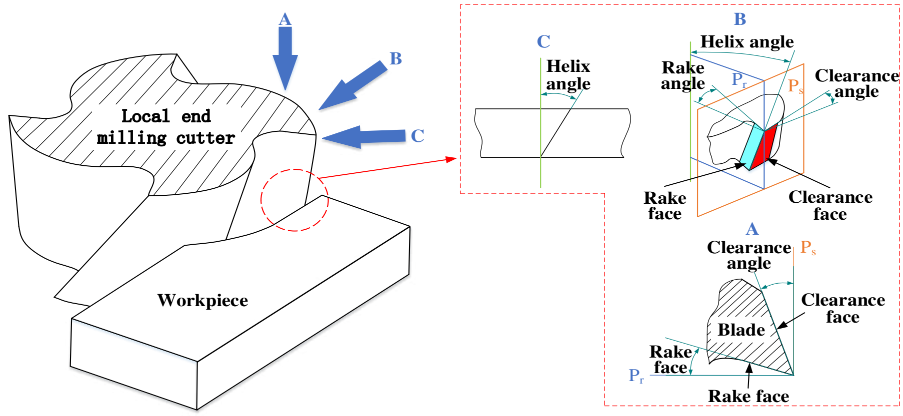


Fig. 6 Tool parameters

These parameters are taken as horizontal factors of orthogonal test to carry out the test planning [24]. Ignoring the interaction between parameters, the SPSS software was used to design the orthogonal test with 7 factors and 3 levels. Accordingly, the parameter level table of $L_{18}(3^7)$ orthogonal test was obtained as shown in Table 4. Moreover, Table 5 presents the corresponding orthogonal simulation test table.

Table 4 Parameter levels

	Rake angle(°)	Clearance angle(°)	Helix angle(°)	Cutting speed(m/min)	Feed per tooth(mm/z)	Cutting depth(mm)	Cutting width(mm)
1	5.00	8.00	30.00	31.40	0.05	1.00	0.1
2	8.00	10.00	33.00	37.68	0.10	2.00	0.2
3	10.00	12.00	35.00	47.10	0.15	3.00	0.3

Table 5 Orthogonal test table

	Rake	Clearance	Helix	Cutting	Feed per	Cutting	Cutting

	angle(°)	angle(°)	angle(°)	speed(m/min)	tooth(mm/z)	depth(mm)	width(mm)
1	10.00	12.00	30.00	31.40	0.10	2.00	0.20
2	5.00	8.00	30.00	31.40	0.05	1.00	0.10
3	10.00	10.00	30.00	47.10	0.05	1.00	0.30
4	8.00	8.00	30.00	37.68	0.15	2.00	0.30
5	10.00	8.00	33.00	37.68	0.15	1.00	0.20
6	5.00	12.00	33.00	37.68	0.05	2.00	0.10
7	8.00	12.00	30.00	47.10	0.15	3.00	0.10
8	10.00	10.00	33.00	31.40	0.15	3.00	0.10
9	5.00	8.00	33.00	47.10	0.10	3.00	0.30
10	5.00	10.00	35.00	31.40	0.15	2.00	0.30
11	10.00	12.00	35.00	37.68	0.05	3.00	0.30
12	8.00	8.00	35.00	31.40	0.05	3.00	0.20
13	5.00	12.00	35.00	47.10	0.15	1.00	0.20
14	10.00	8.00	35.00	47.10	0.10	2.00	0.10
15	8.00	10.00	35.00	37.68	0.10	1.00	0.10
16	5.00	10.00	30.00	37.68	0.10	3.00	0.20
17	8.00	10.00	33.00	47.10	0.05	2.00	0.20
18	8.00	12.00	33.00	31.40	0.10	1.00	0.30

3.4.2 Setting of performance indicators

In the metal cutting process, tool wear is defined as the material loss or deformation of the contact surface caused by friction between the cutting tool and the workpiece. Generally, the tool wear can be mainly divided into adhesive wear, abrasive wear, fatigue wear, corrosion wear and fretting wear [25]. In the evaluation indicator of the milling cutter performance, cutter life is an important indicator. Therefore, it is of significant importance to select the right-wear model when machining to a certain distance. Since carbide the cutting tool forms a complex thermal coupling, different forms of wear and tear may appear at different temperatures. In particular, diffusion and adhesion wear appear at low cutting temperatures [26]. Therefore, the Usui wear model is adopted in this paper, and its form is shown in Eq. 9,

$$\frac{dW_{\text{Adhesion wear}}}{dt} = A_w \cdot \sigma_n \cdot v_c \cdot e^{\left(\frac{-B_w}{273+T}\right)} \qquad (9)$$

where σ_n is positive pressure, v_c is the chip slip velocity and T is the tool temperature. Moreover, A_w and B_w are the wearing characteristic constants, which can be obtained through the tool wear test. In this article, these parameters are set to A_w=0.0004 [27] and B_w=7000 [28].

The workpiece cut by end milling cutter is block workpiece. Accordingly, the formula of material removal amount V within a certain time is shown in Eq. 10,

$$V = v_f \cdot t \cdot a_p \cdot a_e = \frac{n \cdot f_z \cdot z}{60} \cdot t \cdot a_p \cdot a_e \qquad (10)$$

where n is the spindle speed, z is the number of teeth and t denotes the cutting time.

3.5 Finite element simulation results

Fig. 7 illustrates obtained results from Deform-3D software for the tool wear rate of 10mm machining. Then the material removal amount during 30 seconds of end milling cutter processing is calculated based on Eq. (10). Table 6 presents the obtained tool wear rate and material removal amount.

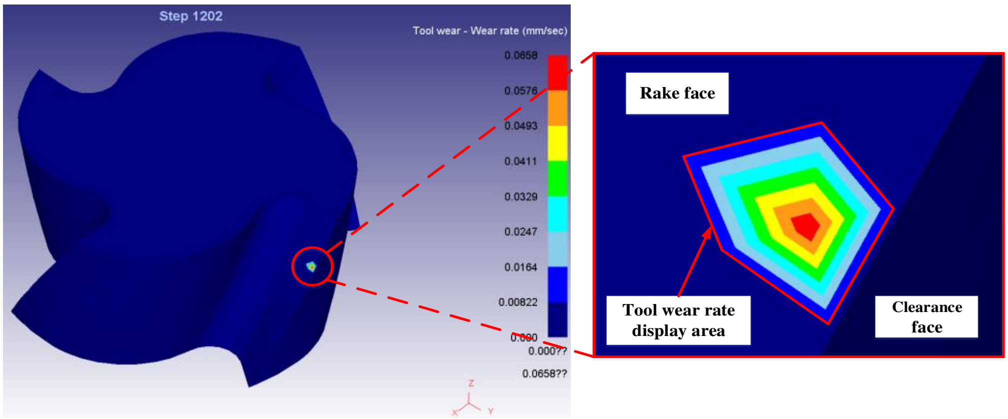


Fig. 7 Simulation results of the tool wear rate

Table 6 Performance indicator data table

Num	Wear rate(mm/s)	V(mm^3)	Num	Wear rate(mm/s)	V(mm^3)
1	0.2370	80	10	0.0189	180
2	0.0250	10	11	0.0811	108
3	0.0370	45	12	0.0067	60
4	0.3280	216	13	0.0758	90
5	0.0019	72	14	0.0167	60
6	0.0207	24	15	0.0318	24
7	0.0658	30	16	0.0158	36
8	0.0563	90	17	0.2050	60
9	0.0196	270	18	0.0028	60

3.6 Calculating the parameter importance

3.6.1 Calculation of weight allocation based on the analytic hierarchy process

(1) Determination of the performance indicator matrix

In order to simplify the writing, tool wear rate and material removal amount are shown as y_1 and y_2, respectively. In literature [29], the weight division ratio of each performance indicator is the same. Meanwhile, tool wear is one of the important factors in the manufacturing process so that many investigations have been carried out to prolong the tool wear life by limiting the tool wear rate [30]. In literature [31], tool life is an important criterion for evaluating tool performance. The wear of the rear surface is chosen as the tool life evaluation indicators, so the tool wear rate has an important effect on the tool life. Table 7 presents the importance comparison scale values of indicators.

Table 7 Importance scale values of indicators

y_j/y_k	y_1/y_2	y_2/y_2
U_{jk}	3/2	1

(2) Calculating the weight value of y_2

$$P_2 = (U_{12} + U_{22})^{-1} = \left(\frac{3}{2} + 1\right)^{-1} = \frac{2}{5}$$

(3) Calculating the weight value of y_1

$$P_1 = P_2 \cdot U_{12} = \frac{2}{5} \cdot \frac{3}{2} = \frac{3}{5}$$

It is found that the weight value of the tool wear rate is $\frac{3}{5}$, the weight value of material removal amount is $\frac{2}{5}$

so that the indicator weight matrix is P={$\frac{3}{5}$, $\frac{2}{5}$}.

3.6.2 Solving membership degree based on the grey correlation method

(1) Preprocessing of an indicator set

Based on the pretreatment process in 2.3.1, the simulation values of tool wear rate and material removal amount in Table 3 are processed to obtain the matrix H, which is required for solving the comprehensive evaluation matrix R. The matrix H can be expressed as follows:

$$H = \begin{bmatrix} 0.5159 & 0.3437 \\ 0.4805 & 0.3818 \\ 0.3861 & 0.5535 \\ 0.5173 & 0.3333 \\ 0.4106 & 0.5337 \\ 0.3696 & 0.3354 \\ 0.6102 & 0.4165 \end{bmatrix}$$

(2) Solving the membership degree based on the grey relational degree

Based on the grey correlation degree in 2.3.2, the membership degree can be solved and accordingly, the comprehensive evaluation matrix R is obtained in the form below:

$$R = \begin{bmatrix} 0.4512 & 0.5203 & 0.8813 & 0.4489 & 0.7458 & 1.0000 & 0.3333 \\ 0.3441 & 0.3907 & 1.0000 & 0.3333 & 0.8476 & 0.3355 & 0.4456 \end{bmatrix}$$

3.6.3 Fuzzy judgment

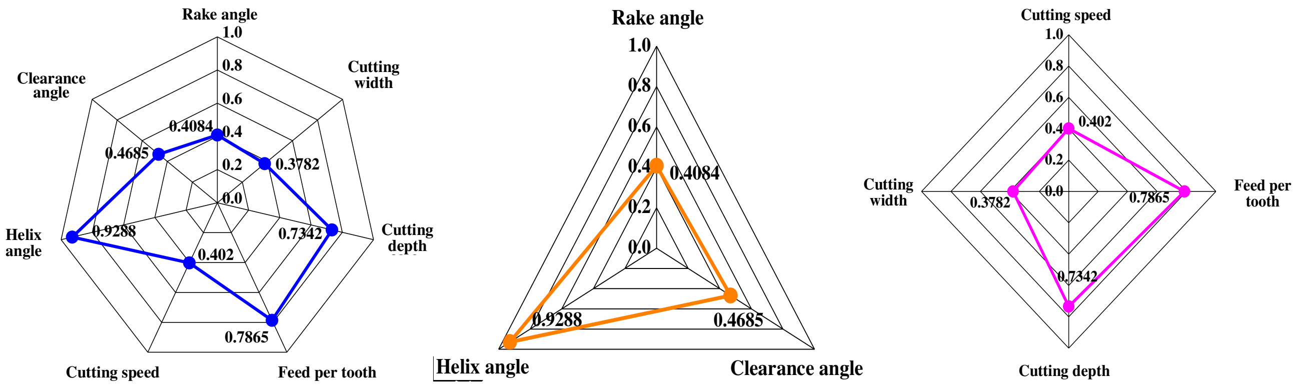
According to the fuzzy judgment calculation in 2.4, the fuzzy judgment matrix B is finally obtained as follows:

$$B = \begin{bmatrix} 0.4084 & 0.4685 & 0.9288 & 0.4020 & 0.7865 & 0.7342 & 0.3782 \end{bmatrix}$$

Based on the foregoing discussions, the importance order of different parameters on the wear rate and material removal amount are helix angle-feed per tooth-cutting, depth-clearance, angle-rake, angle-cutting and speed-cutting width.

3.7 Importance radar chart of parameters

Radar chart analysis is a graph-based multivariable comparative analysis technology to reflect information and project multi-dimensional data onto a plane, which is widely applied to visualize multi-dimensional data [32]. In this section, the radar chart method is applied to express the comprehensive evaluation results of tool parameters and operating parameters on tool wear rate and material removal amount. In the presented radar chart in Fig. 8, it is observed that the helix angle and the cutting width have the highest and lowest importance among the studied performance indicators. Moreover, it is found that the clearance angle and helix angle among tool parameters and the cutting depth and feed per tooth among operating parameters are of the highest importance to the studied performance indicators. Therefore, in the case of end milling cutter side milling titanium alloy, the correlation among the shape parameters, performance indicators and use parameters of the tool is obtained. Subsequently, the clearance angle, helix angle, feed per tooth and cutting depth are selected as the influence parameters, and the correlation between the tool wear rate and material removal is studied.



(a) Radar map of all parameters (b) Radar map of tool parameters (c) Radar map of operating parameters

Fig. 8 Importance radar map of different parameters

4 Parameter level optimization of the milling performance

4.1 Range analysis

Studies reveal that the Range analysis is an effective scheme to analyze test results [33]. The range value R reflects the influence degree of each factor on the test indicators at different levels. The greater the range value, the greater the influence of the corresponding factor on the indicators, and the more important the factor [34]. The range value R is mathematically expressed as Eq. 11,

$$R_j = \max_{1\le s\le u}\left(\frac{K_{sj}}{u}\right) - \min_{1\le s\le u}\left(\frac{K_{sj}}{u}\right) \qquad (11)$$

where R_j (j=1,2,3,...,n) is the range value of the j^{th} parameter, K_{sj} is the sum of the values of the earned performance indicators of the s^{th} level of the j^{th} parameter in the orthogonal table, and u is the level number of parameters.

4.2 Range analysis of performance indicators

Table 8 Range analysis table of the tool wear rate

	Rake angle	Clearance angle	Helix angle	Cutting speed	Feed per tooth	Cutting depth	Cutting width
k1	0.0293	0.0695	0.1181	0.0578	0.0626	0.0291	0.0361
k2	0.1067	0.0608	0.0511	0.0799	0.0540	0.1377	0.0904
k3	0.0717	0.0805	0.0385	0.0700	0.0911	0.0409	0.0812
R	0.0774	0.0197	0.0796	0.0221	0.0371	0.1086	0.0543

Table 9 Range analysis table of the material removal amount

	Rake angle	Clearance angle	Helix angle	Cutting speed	Feed per tooth	Cutting depth	Cutting width
k1	101.67	114.67	69.50	80.00	51.17	50.17	39.67
k2	75.00	72.50	96.00	80.00	88.33	103.33	66.33
k3	75.83	65.33	87.00	92.50	113.00	103	146.50
R	26.67	49.34	26.50	12.50	61.83	53.16	106.83

Extreme R-values in Tables 8 and 9 reveal that for the rate of tool wear in the cutting tool parameters and use order of importance for cutting depth-helix angle-rake angle-cutting width- feed per tooth-cutting speed-clearance angle. It is inferred that the cutting depth and the clearance angle are the most and least important indicators of the tool wear rate, respectively. For material removal, the importance order of tool and operating parameters is the cutting width, cutting depth, clearance angle, feed per tooth, rake angle-helix and the angle-cutting speed. Accordingly, it is found that the cutting width is the most important indicator of the material removal, while the cutting speed is the least important one.

4.3 Range analysis and comparative analysis of the evaluation results

According to sections 2.4.3 and 3.2, the cutting depth plays an important role in both unilateral analysis and comprehensive evaluation of tool wear rate and material removal amount for the four parameters with the highest importance in the comprehensive evaluation results. However, there are some differences in the importance of helix angle and feed per tooth, which are at the forefront of the comprehensive evaluation, but they are in the lower position in range analysis. Since the feed has an important role in tool wear and material removal rate, and the helix angle and tool life have a strong correlation, it is concluded that the helix angle and the feed per tooth have an important role in tool wear rate and material removal. Therefore, this modern evaluation method is applied to comprehensively evaluate the performance indicator.

The issue can also be studied from the following viewpoints: Firstly, the range analysis is based on the existing data in the orthogonal table for evaluation, so any variation in the number of levels can simply affect the analysis accuracy. Secondly, in the range analysis, only the maximum and minimum values of the performance indicator at the same parameter and different levels are selected. In other words, intermediate values, which have a certain impact on the analysis accuracy are ignored. Finally, the metal cutting process is a fuzzy system, where there are remarkable interactions between various performance indicators. However, the range analysis cannot be applied to perform accurate analysis under the fuzzy system, which adversely affects the accuracy.

4.4 Parameter level optimization

According to Table 8, the cutting depth has the greatest and most important influence on the wear rate. Furthermore, the rake angle and helix angle have the same influence on the wear rate, while the clearance angle has the least influence on it. Fig. 9 shows different levels for the influence of different parameters on the wear rate. It is observed that the wear rate reaches the lowest, but because of the cutting speed, clearance angle after less effect on the wear rate, so the cutting speed of D3 level and clearance angle of B1 level also can be used as an option.

In summary, the best combination of the orthogonal test is the rake angle of 5°, the clearance angle of 10°, the helix angle of 35°, the cutting speed of 31.4m/min, the feed per tooth of 0.10mm/z, the cutting depth of 1mm and the cutting width of 0.1mm. In addition, cutting speed of 47.1m/min and clearance angle of 8° are available as alternative levels.

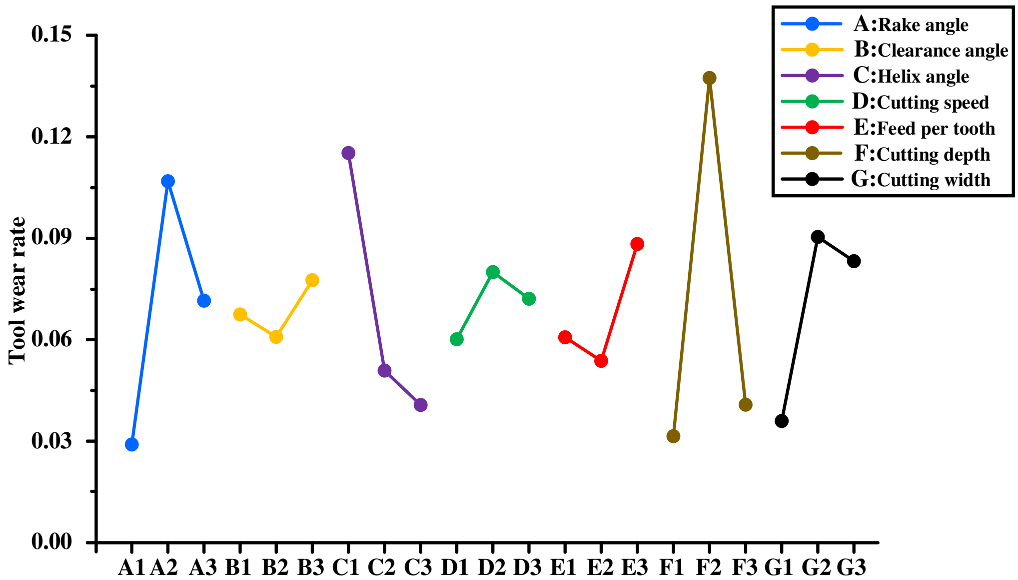


Fig. 9 Factor - index diagram of different factors and levels on the tool wear rate

Table 9 indicates that the cutting width has the highest influence on the material removal amount, while the cutting speed has the least influence on it. Fig. 10 illustrates a binary diagram of the influence of different parameters at different levels on the material removal amount. When parameters are set to A1, B1, C2, D3, E3, F2, the material removal volume achieves the maximum G3. However, the cutting speed and helix angle have less

influence on the material removal amount so the cutting speed of D1 and D2, helix angle of C3 level can be used as an option. Fig. 10 indicates that the material removal amounts at F2 and F3 levels are very close so the F3 level of cutting depth can also be used as an option.

It is concluded that the best combination of the orthogonal test is the rake angle of 5°, clearance angle of 8°, helix angle of 33°, cutting speed of 47.1m/min, feed per tooth of 0.15mm/z, the cutting depth of 2mm and the cutting width of 0.3mm. In addition, the cutting speed can be 31.4m/min or 37.68m/min, the helix angle and cutting depth are also available at 35° and 3mm as alternative levels.

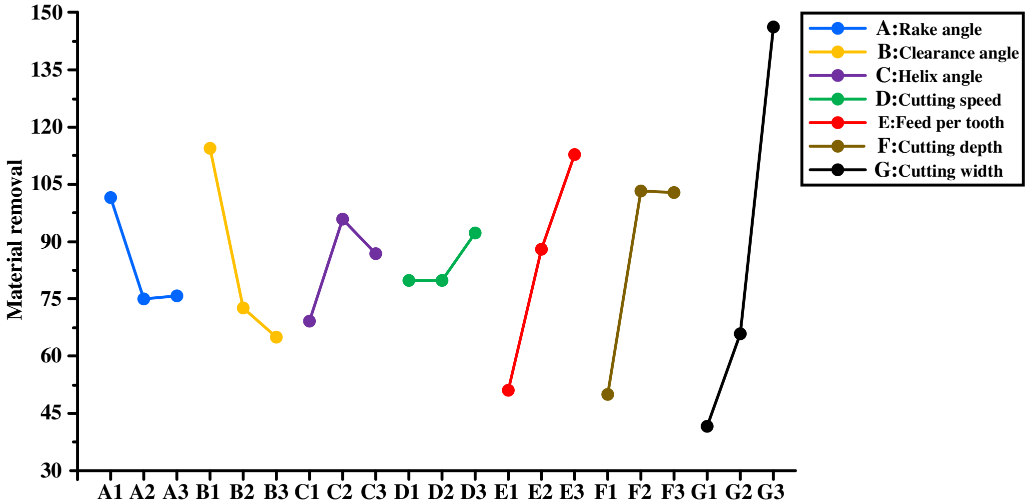


Fig. 10 Factor-index diagram of material removal amount by different factors and levels

5 Conclusion

In order to facilitate the accurate research of the correlation among the tool shape parameters, performance indicators and operating parameters in the milling process of titanium alloy, it is necessary to select the most important tool parameters and operating parameters as performance indicators. In this paper, the analytic hierarchy process (AHP) and grey-fuzzy evaluation method are used to evaluate the importance of tool parameters and operating parameters on tool wear rate and material removal. According to the orthogonal test table, the best level combination of different parameters is selected by the range analysis method. Based on the obtained results, the main conclusions of this article can be summarized as follows:

(1) The helix angle has the greatest importance on the tool wear rate and material removal, followed by the feed per tooth, cutting depth, clearance angle, rake angle, cutting speed and the cutting width. The cutting width has the lowest importance parameter.

(2) It is found that the evaluation results obtained from the evaluation method are more accurate. Therefore, this method is applied to perform the analytic hierarchy process, and the grey-fuzzy evaluation method is used to comprehensively evaluate multiple performance indicators with different parameters.

(3) Among the studied indicators, the importance of the cutting depth to tool wear rate is the largest, while that of the clearance angle is the smallest. It is found that the lowest tool wear rate can be reached for the rake angle of 5°, the clearance angle of 10°, the helix angle of 35°, the cutting speed of 31.4 m/min, the feed per tooth of 0.10 mm/z, the cutting depth of 1mm and the cutting width of 0.1 mm.

(4) The cutting width and the cutting speed have the largest and the smallest importance to the material removal. The highest material removal amount can be reached for the rake angle of 5°, clearance angle of 8° and helix angle of 33°, cutting speed of 47.1 m/min, feed per tooth of 0.15 mm/z, cutting depth of 2mm and the cutting width of 0.3mm.

(5) In this paper, the performance indicator value is obtained through simulation, but there is a certain error between the simulation value and the experimental value. Therefore, under the condition of sufficient time and funding in the future, the required tool wear rate and material removal amount can be obtained through

experiments, so as to make the evaluation results more accurate.

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Figures

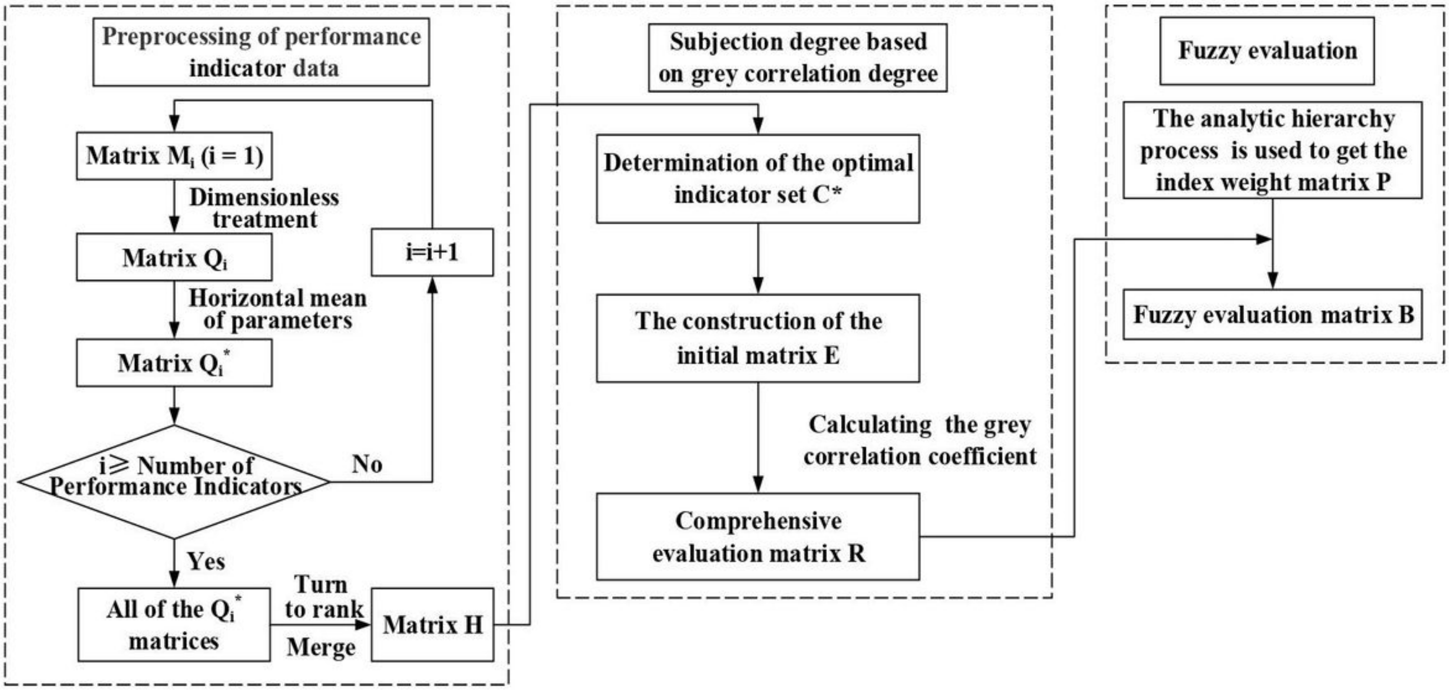


Figure 1

Improved importance evaluation flowchart

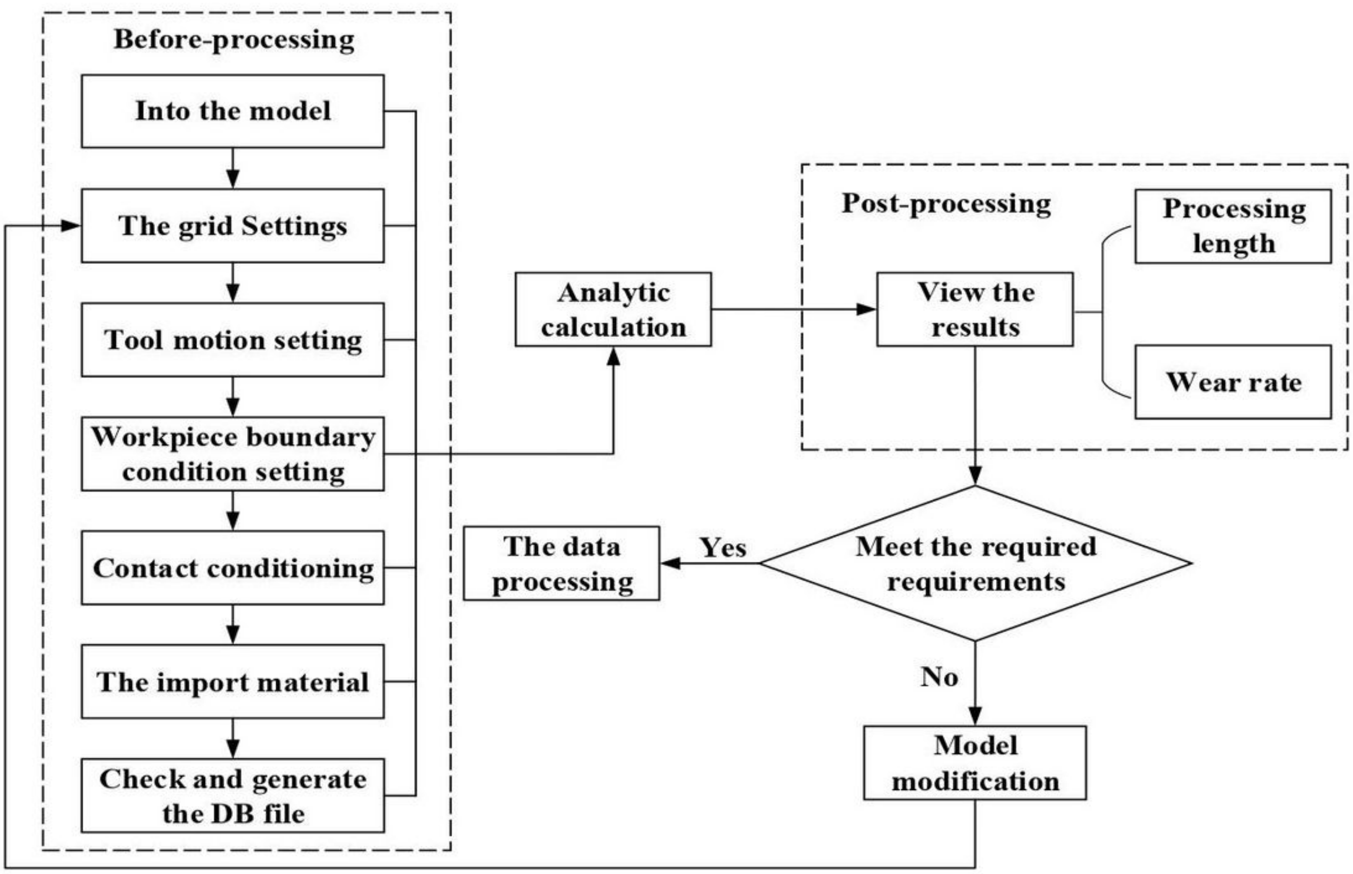
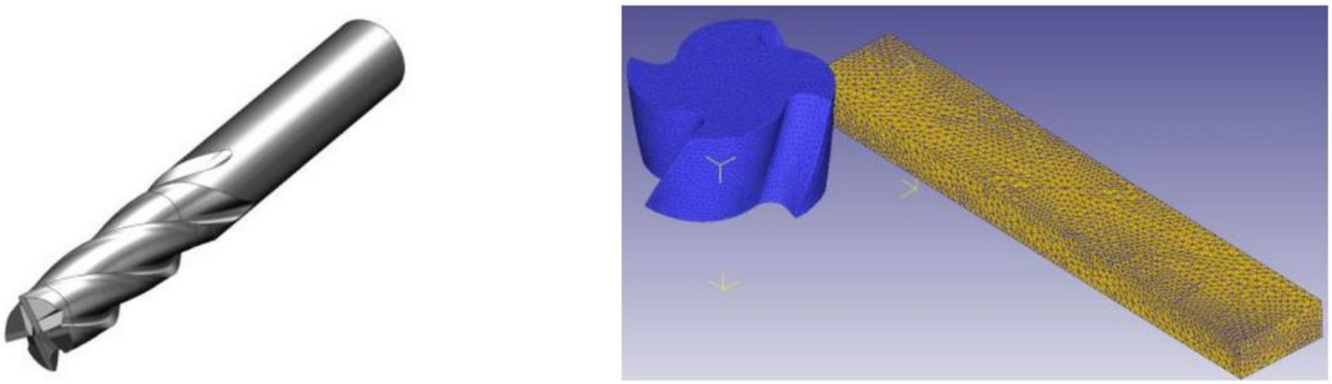


Figure 2

Cutting simulation flowchart of DEFORM_3D software



(a) End milling cutter model (b) The simulation model

Figure 3

Simulation model of the side milling process

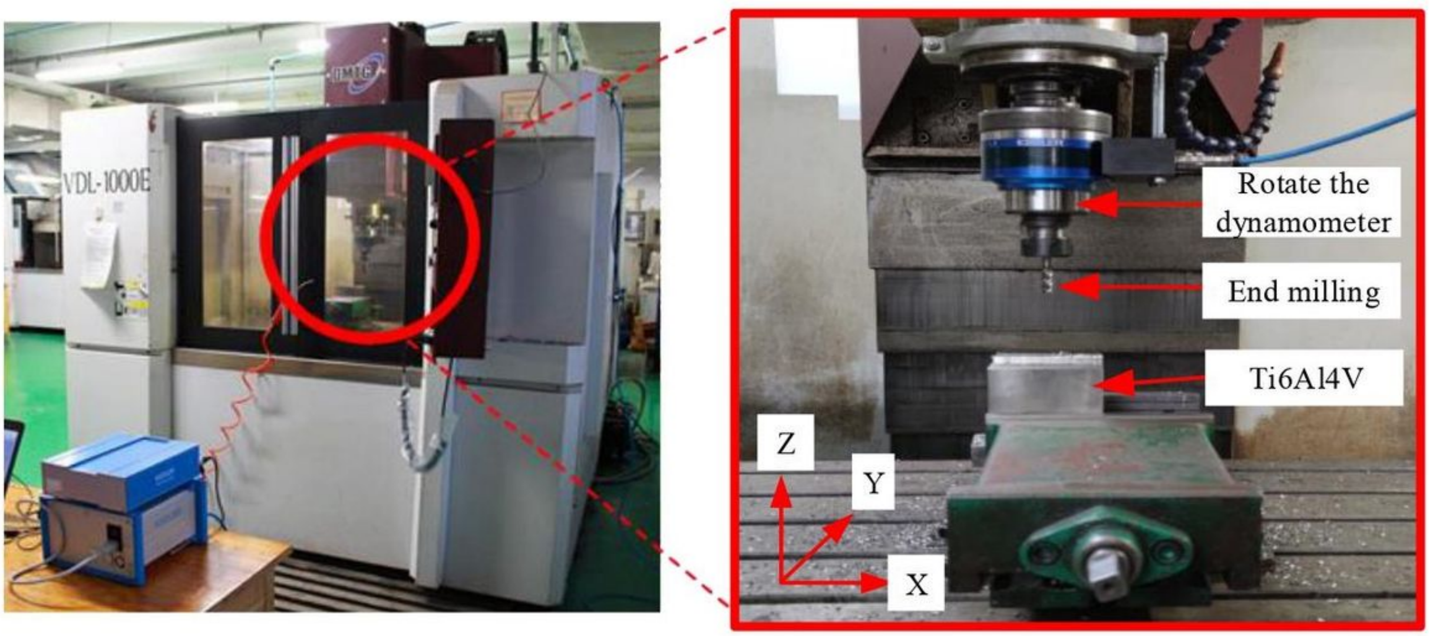


Figure 4

Experimental instruments and equipment used in the experiment

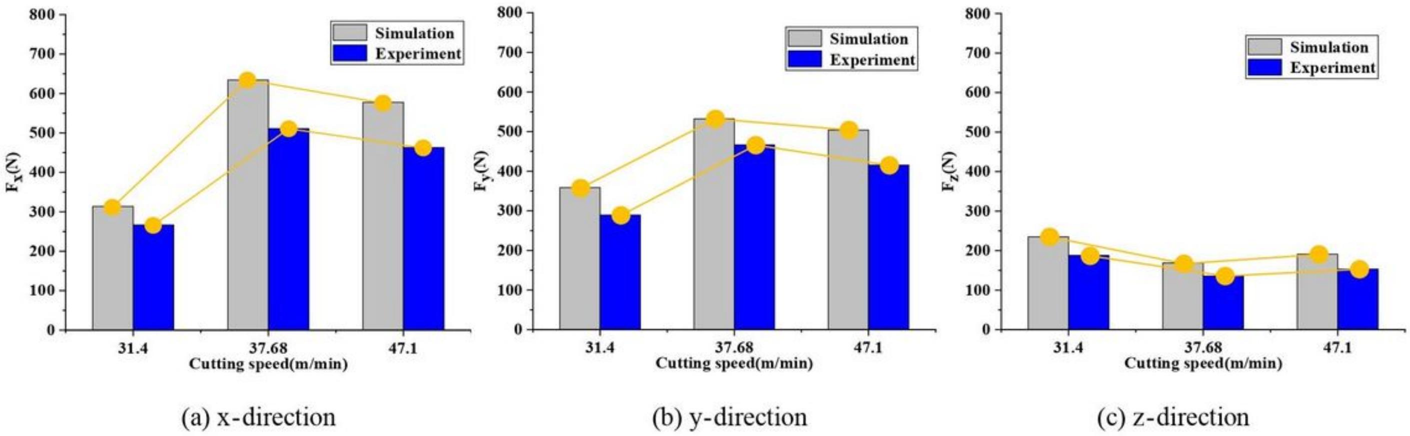


Figure 5

Cutting forces along different directions

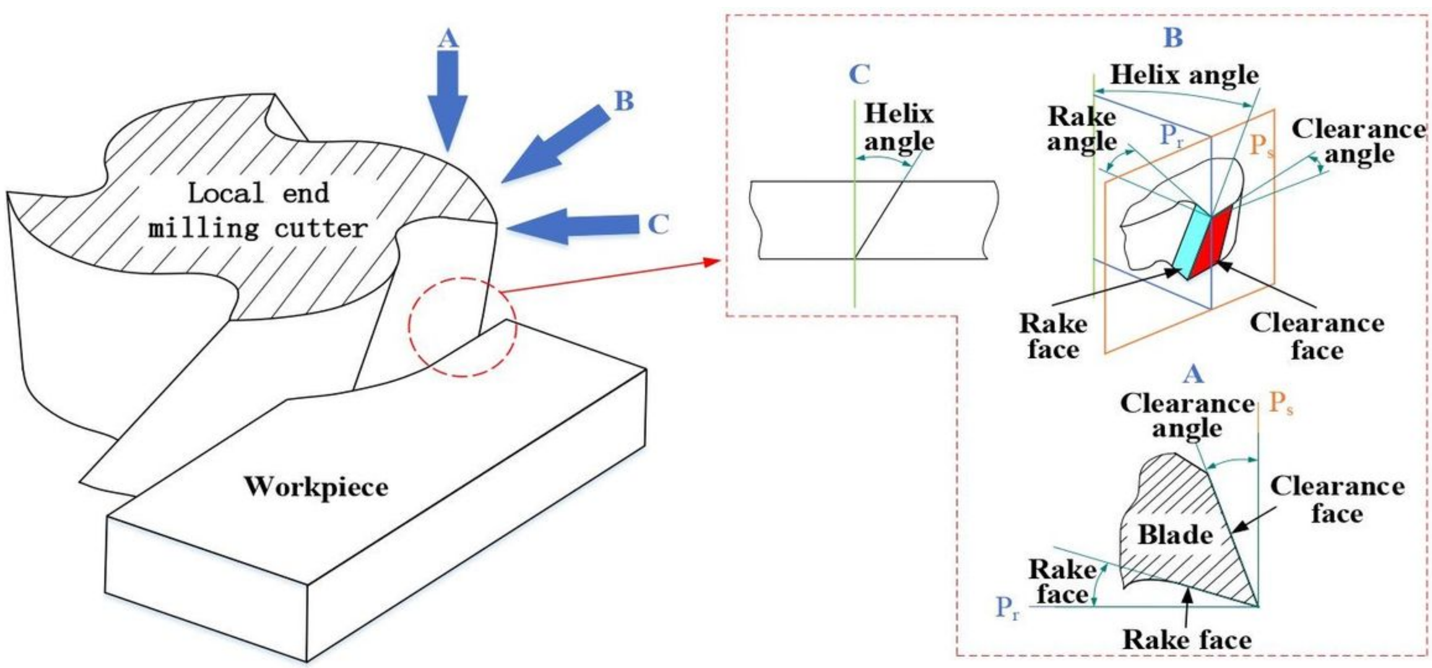


Figure 6

Tool parameters

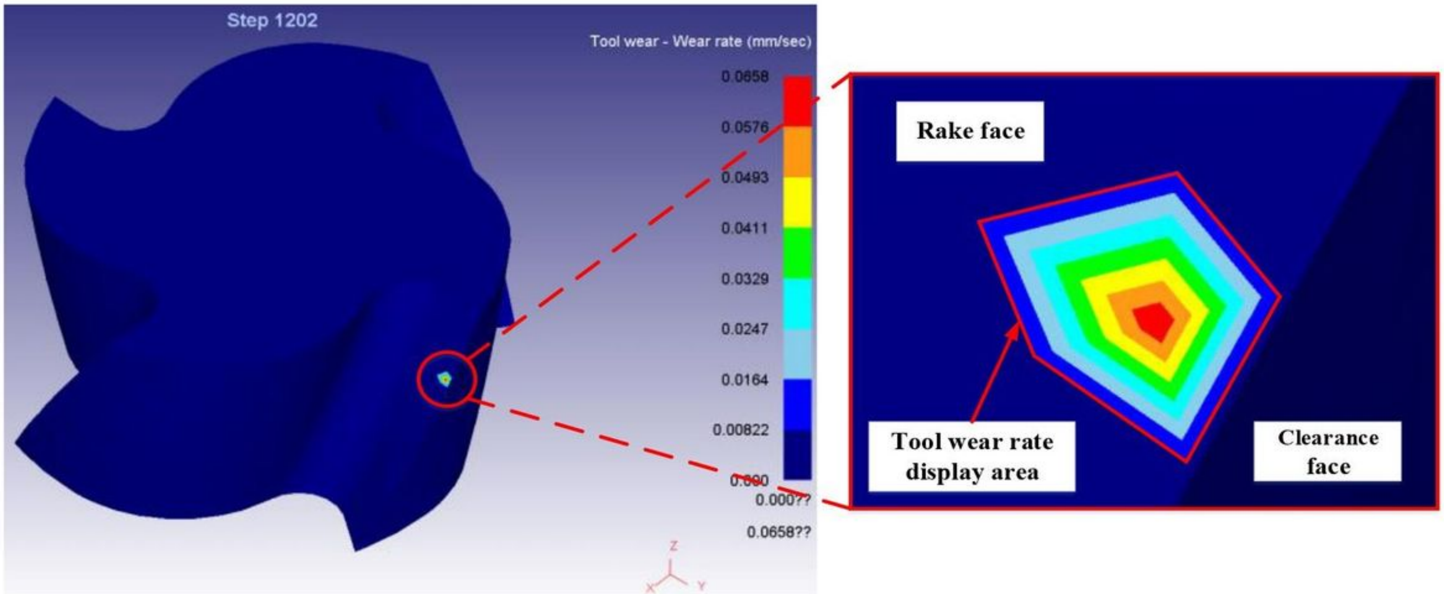


Figure 7

Simulation results of the tool wear rate

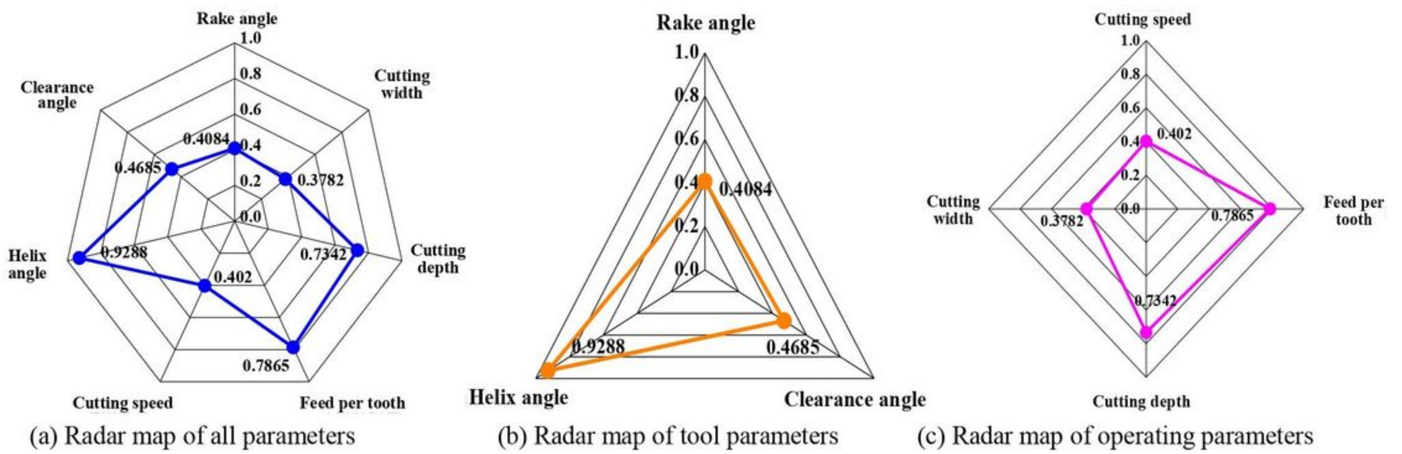


Figure 8

Importance radar map of different parameters

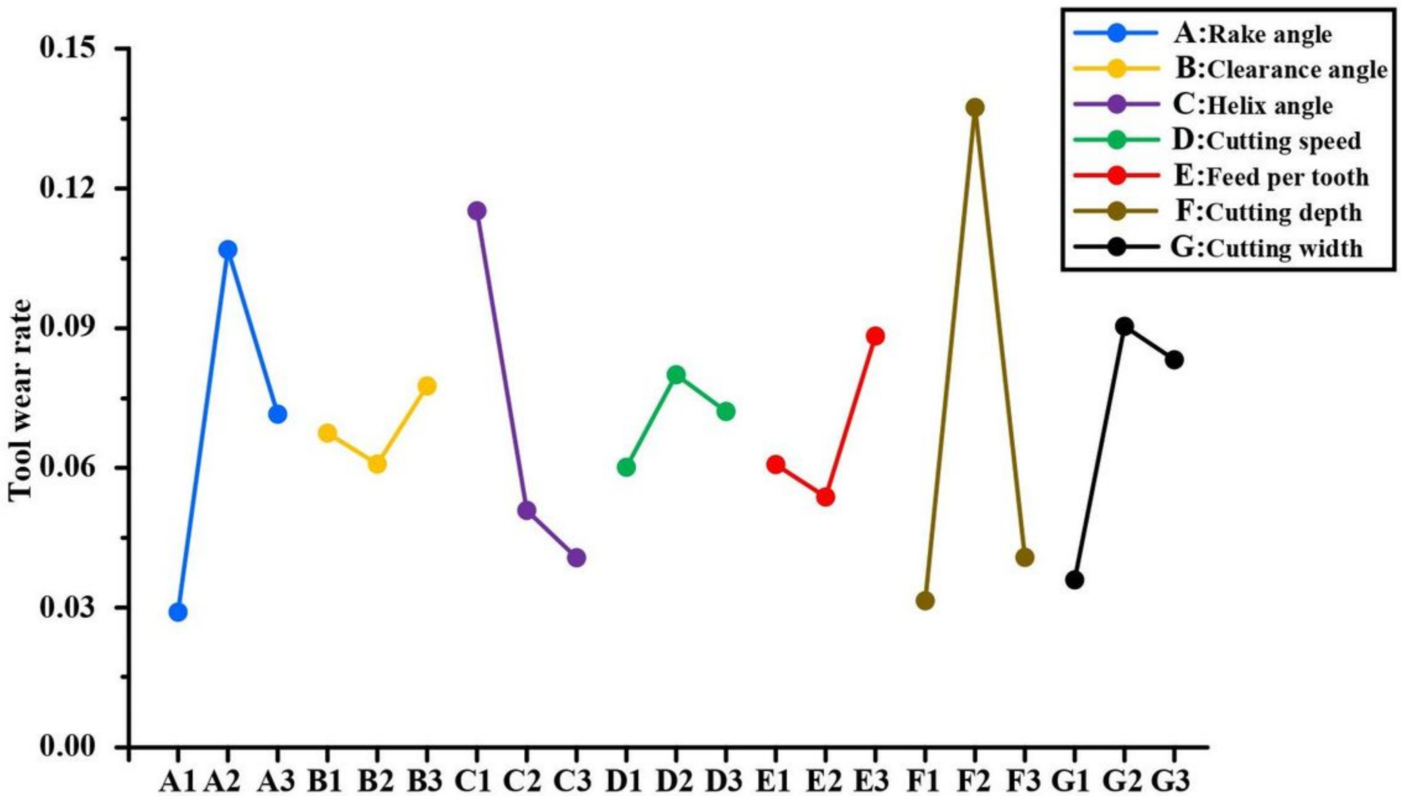


Figure 9

Factor - index diagram of different factors and levels on the tool wear rate

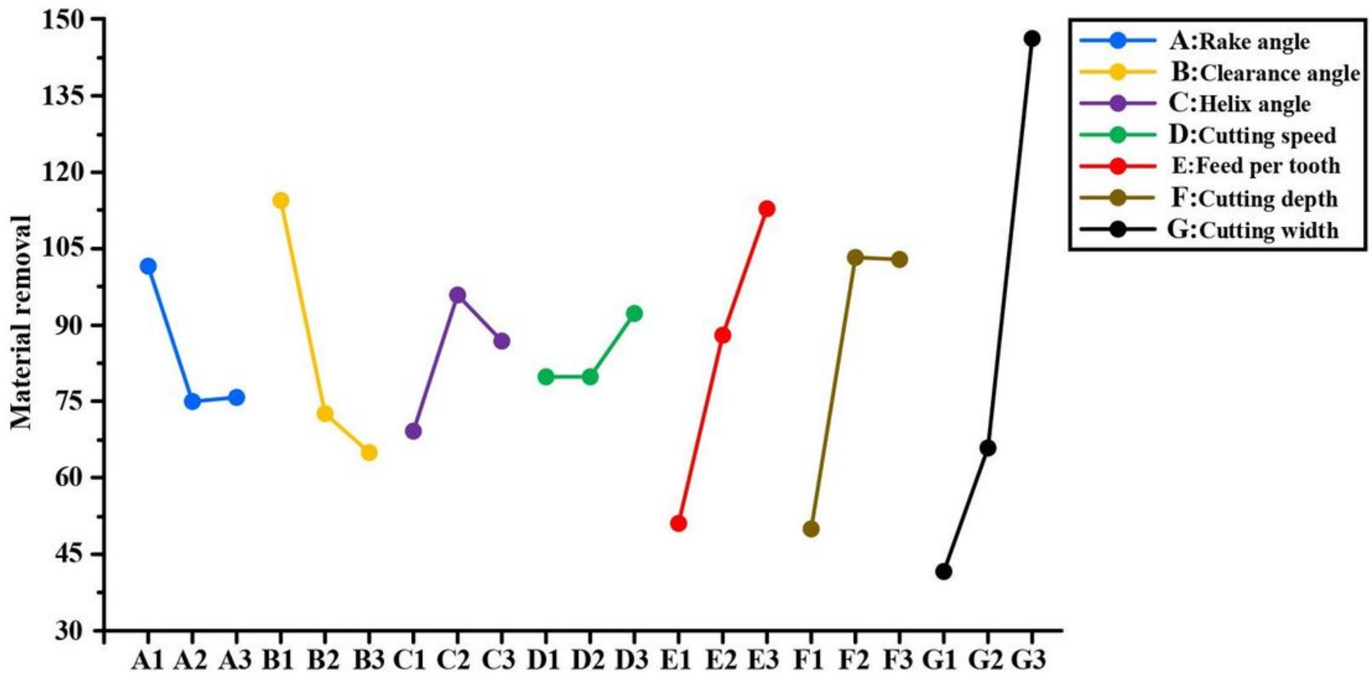


Figure 10

Factor-index diagram of material removal amount by different factors and levels