Optimization of Machining Parameters in Blisk Processing Based on Tool Reliability

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Abstract: Machining parameters are essential factors affecting the machining efficiency and tool life. Tool reliability varies with the process. Tool reliability affects the life of the tool, and then impacts the processing quality and manufacturing cost. Therefore, machining parameters optimization considering tool reliability is essential and scientific. In this paper, firstly the reliability model of tool life was solved by Markov Chain Monte Carlo (MCMC) method. Then taking the average tool life as the constrain condition, a multi-objective optimization algorithm that integrates the gray correlation analysis (GRA), radial basis neural network (RBF) and particle swarm optimization (PSO) algorithm (GRA-RBF-PSO) was used to search for optimal machining parameters of blisk-tunnel processing. At last, experiments were carried out to validate optimized results. The experimental results indicated that the reliability-based optimization of machining parameters can effectively improve the tool life and as well as ensure smaller cutting force and larger material removal rate during blisk-tunnel processing.

1. Introduction

With the development of society and the progress of science and technology, Aerospace technology has become an important index to measure a country's scientific and technological level. The blisk is the core component of the new generation aero-engine to realize the structure innovation. It integrates the blade and disc leaving out mortise and tenon. It provides effective guarantee for improving overall performance, simplifying structures, reducing weight and series, improving durability and reliability of aero engines. The blisk has complex blade profile, deep and narrow tunnels, high machining accuracy. The blisk is usually made of difficult-to-process materials. Therefore, the processing of blisk is very difficult [1, 2].

The mature manufacturing techniques of blisk include electron beam welding [3], linear friction welding [4], electrochemical machining [5], multi-axis CNC milling. The multi-axis CNC milling is commonly used. To improve the processing efficiency of blisk, the processing scheme of the disc, plunge and side milling was put forward by our research group. Disc milling is used for rough machining of blisk-tunnels. The material removal rate of disc milling is large, which shortens the processing time and improves the machining efficiency. However, in the process of disc milling, the tool is under great force, the tool wear is serious and the tool life is shortened leading to increase of processing costs. Therefore, it is a key problem to reduce tool wear and prolong tool life by selecting appropriate machining parameters for disc milling. In this paper, the optimization of machining parameters in disc milling process of blisk-tunnels was studied with the constraint condition of mean
tool life.

The tool life is a virtual index in its reliability evaluation. It is very necessary to take it as one of the constraints when optimizing the processing parameters. The main factors affecting tool life are cutting speed, feeding rate and cutting depth [7]. A lot of research has been done on tool life. Yang et al. carried out theoretical and experimental research on the reliable life of cemented carbide cutting tools and established mathematical models to evaluate the reliability of the tool life [8]. Chen et al. proposed to use the Logistic regression model to evaluate the reliability of tool life [9]. A life assessment method was developed for the tool remaining service life based on the Wiener process by Sun et al. [10]. Liu et al. put forward the fuzzy reliability evaluation method for tool [11]. An approximate method was used to evaluate the reliability of the tool life by Salonitis et al. [12].

The prediction of tool life cannot only consider the distribution of the tool life but also ignore the influence of cutting parameters. The Cox proportional hazard model can integrate the statistical distribution and the impact of reliability, which is very suitable for the reliability analysis of the tool life. However, there are many parameters in Cox proportional hazard model, which cannot be estimated by the traditional maximum likelihood method. Based on Bayes' theorem, Markov Chain Monte Carlo (MCMC) simulation method was applied to solve the difficulty of estimating parameters and obtain a reliability model for tool life[7].

In the milling process, cutting force and material removal rates affect the machining cost and efficiency. The larger cutting force corresponds to the higher material removal rate leading to shorten the tool life. The smaller cutting force corresponds to lower material removal rate resulting in extending the tool life and low processing efficiency [13]. Therefore, the cutting force and material removal rate are two contradictory variables and can be used as two objective variables for the optimization of machining parameters. In the previous research, cutting force and material removal rate were taken as the target variables to optimize the parameters of disc milling of blisk-tunnels, but the influence of tool life was not considered [14]. The optimized machining parameters were obviously unreasonable. Therefore, based on the previous research, the average tool life was taken as the constraint to optimize the machining parameters of disc milling blisk-tunnels in this paper. The Markov chain Monte Carlo (MCMC) method was applied to evaluate the parameters in the reliability model, the average tool life is used as constraint, and the grey relational analysis (GRG), the radial basis function network(RBF) and the particle swarm optimization algorithm(PSO) to find the optimal machining parameters combination(GRG).

The remainder of this paper is arranged as follows. The life reliability model of tool was established in Section 2. Section 3 introduces the grey correlation analysis method, radial basis function network and the particle swarm optimization algorithm. Experimental validation was displayed in Section 4. Section 5 and 6 lists the conclusions.

2. The reliability assessment method based on weibull proportional hazards model

The commonly used models for tool reliability evaluation include stochastic process model, regression model, fuzzy theory, Weibull distribution model, statistical analysis method and etc. Weibull distribution is usually used to evaluate the tool life. Tool life is also affected by the cutting parameters [15]. Therefore, the two-parameter Weibull distribution combination of proportional hazard model is used to evaluate the tool reliability.

The probability density function (PDF) of a two-parameter Weibull distribution is expressed as:

$$ f(t) = \frac{\beta}{\eta} \left(\frac{t}{\eta}\right)^{\beta-1} \exp\left[-\left(\frac{t}{\eta}\right)^{\beta}\right] $$

(1)

$t$ represents tool failure time, which refers to the average abrasion on the flank surface of the tool with 0.3 mm and the maximum abrasion with 0.6 mm. $\beta$ is shape parameter, $\eta$ represents size parameter.
Setting $\lambda = 1/\eta^\beta$, equation (1) can be simplified as:

$$f(t) = \lambda t^{\beta-1} \exp(-\lambda t^\beta) \quad (2)$$

The corresponding failure rate and reliability can be expressed as:

$$h_b(t) = \lambda t^{\beta-1} \quad (3)$$

$$R(t) = \exp(-\lambda t^\beta) \quad (4)$$

Cutting parameters have a great impact on the tool reliability. Taylor tool life index equation is usually used to predict the tool life, but it has certain limitations. In order to comprehensively consider the influence of cutting parameters on tool life, a tool reliability evaluation model was established by combining Weibull distribution [15] with proportional hazard model [16]. The failure rate of tool can be calculated as:

$$h(t) = h_0(t) \exp Z = h_0(t) \exp \left(\ln \nu - \ln f - \ln d \right) \quad (5)$$

Where $\eta_1$, $\eta_2$ and $\eta_3$ are model parameters. $\nu$, $f$ and $d$ represent cutting rate, feeding rate per tooth, cutting depth and $Z = -\eta_1 \ln \nu - \eta_2 \ln f - \eta_3 \ln d$, respectively.

The PDF of tool life can be written as:

$$f(t) = \lambda t^{\beta-1} \exp(Z - \lambda t^\beta \exp Z) \quad (6)$$

Therefore, the likelihood function of the tool failure time when using different cutting parameters can be represented as:

$$L = \prod_{i=1}^{n} f(t_i) = \prod_{i=1}^{n} \left[ \lambda t_i^{\beta-1} \exp(Z - \lambda t_i^\beta \exp Z) \right] \quad (7)$$

Additionally, the log-likelihood function of equation (6) can be expressed as:

$$\ln L = n \left( \ln \lambda + \ln \beta \right)$$

$$+ \sum_{i=1}^{n} \left[ (\beta - 1) \ln t_i + Z_i - \lambda t_i^\beta \exp Z_i \right] \quad (8)$$

Equation (8) includes five parameters, a complex system of equations can be obtained and the analytical solution cannot be closed. The MCMC method can be used to simulate and estimate the model parameters [17, 18, 19].

The reliability function can be obtained from equation (5) and equation (6):

$$R(t) = f(t)/h(t) = \exp(-\lambda t^\beta \exp Z) \quad (9)$$

3. Multi-parameter optimization method

In this paper, the grey correlation degree value, radial basis neural network and particle swarm optimization algorithm are combined to search for the optimal parameters of cutting speed ($\nu$), feeding rate per tooth ($f$), and cutting depth ($d$) to determine the best balance between the cutting force and material removal rate, which is equivalent to the largest grey relational grade (GRG). Based on the calculated degree of the gray correlation of the cutting tool, a radial basis neural network can be used to non-linearly map the input data and to calculate the corresponding grey relational grade (GRG) by employing the particle gray optimization algorithm.

3.1. Grey Correlation Analysis

Gray correlation analysis is the normalization of the dimensions of the raw data [22, 23]. Through the calculation of the gray correlation degree, the multi-objective optimization problem can be transformed into a single-objective optimization problem. When the objective function is minimized,
the normalization formula can be shown as:

$$y'_i(k) = \frac{\max y^0_i(k) - y^0_i(k)}{\max y^0_i(k) - \min y^0_i(k)} \quad \text{for } i=1,2,...,m, \quad k=1,2,...,n$$  \hspace{1cm} (10)

Where, $y^0_i(k)$ and $y'_i(k)$ are the original and the normalized sequences of data.

When the objective function is maximized, the normalization formula can be expressed as:

$$y'_i(k) = \frac{y^0_i(k) - \min y^0_i(k)}{\max y^0_i(k) - \min y^0_i(k)} \quad \text{for } i=1,2,...,m, \quad k=1,2,...,n$$  \hspace{1cm} (11)

After the data is normalized, the gray correlation coefficient can be calculated as:

$$\gamma_{ik} = \gamma\left(y'_i(k), y'_j(k)\right) = \frac{m + \xi M}{\Delta_i(k) + \xi M}$$

$$\Delta_i(k) = \left|y^0_i(k) - y^0_j(k)\right| \quad \Delta_i = (\Delta_i(1), \Delta_i(2), \ldots, \Delta_i(n)) \quad \text{for } i=1,2,...,m$$  \hspace{1cm} (12)

Where, $y^0_i(k)$ and $y'_i(k)$ represent the reference and comparison sequences, respectively. $\Delta_i(k)$ expresses the absolute difference between $y'_i(k)$ and $y'_j(k)$. Set $M = \max_i \max_k \Delta_i(k)$, $m = \min_i \min_k \Delta_i(k)$, and $\xi$ is the distinguish function, $\xi \in [0,1]$.

Accordingly, the grey relational grade (GRG) can be calculated as:

$$\gamma_k = \sum_{i=1}^{m} \beta_i \gamma_{ik} \quad k=1,2,...,n, \quad \sum_{i=1}^{m} \beta_i = 1$$  \hspace{1cm} (13)

### 3.2 Radial Basis Function Neural Network

Radial basis function (RBF) neural networks are good at the nonlinear fitting, complex nonlinear relationships mapping, and global or local approximation. Therefore, radial basis neural networks are widely used in the fields of fuzzy recognition, nonlinear fitting, and control [24, 25]. Suppose the RBF consists of $m$ inputs, $n$ outputs and $h$ hidden layer nodes. The input vector of the RBF neural network is $x = [x_1, x_2, \ldots, x_m]$, the output vector of the network is $y = [y_1, y_2, \ldots, y_n]$, hence, the RBF of a Gaussian function can be expressed as:

$$\phi_i(x) = \exp \left[ \frac{-\|x - c_i\|^2}{2\sigma_i^2} \right]$$  \hspace{1cm} (14)

Where $\|x - c_i\|$ represents Euclidean distance, $\sigma_i$ is the width of the first neuron, $c_i$ denotes the data center of the first hidden layer node. Accordingly, the $j$th output of a RBF can be expressed as:

$$y_j = \sum_{i=1}^{h} \beta_{ij} \phi_i(\|x - c_i\|)$$  \hspace{1cm} (15)

Where $\beta \in \mathbb{R}^{h \times p}$ represents the weight of the output matrix.
3.3. Particle Swarm Optimization Algorithm

A particle swarm optimization algorithm (PSO) is designed by simulating the foraging behavior of birds. The PSO is widely used in nonlinear programming and multi-objective optimization. For N-dimensional space optimization problem with the population of \( \left( x_1^{(k)}, x_2^{(k)}, \ldots, x_n^{(k)} \right) \) and each particle contains two variables that are position and velocity. During the iteration process, each particle has a unique extreme value.

\[
x_i^{(k)} = (x_{i1}^{(k)}, x_{i2}^{(k)}, \ldots, x_{in}^{(k)})
\]

represents the position vector of \( i \)th individual at \( k \)th time point. The velocity vector \( v_i^{(k)} = (v_{i1}^{(k)}, v_{i2}^{(k)}, \ldots, v_{in}^{(k)}) \) is the speed of each particle. The position and velocity of each particle in the iterative process of the PSO can be updated by tracking individual and global extreme values.

The position and velocity updates follow a neighborhood function as:

\[
v_{id}^{(k+1)} = \omega v_{id}^{(k)} + c_1 \text{rand} \left( P_{id}^{(k)} - x_{id}^{(k)} \right) + c_2 \text{rand} \left( P_{gd}^{(k)} - x_{id}^{(k)} \right)
\]

\[
x_{id}^{(k+1)} = x_{id}^{(k)} + v_{id}^{(k+1)}
\]

(17)

where \( P_{id}^{(k)} \) is the individual extreme value of \( i \)th particle after experiencing \( k \) time points, \( P_{gd}^{(k)} \) is the global extreme value of \( i \)th particle after experiencing \( k \) time points, \( c_1 \) and \( c_2 \) are learning efficiency, \( \omega \) represents the weight value, \( \text{rand} \) reflects a random number between 0 and 1. There are also restrictions on the speed of particles such as \( |v_{id}^{(k+1)}| < v_{\text{max}} \).

4. Experimental procedures

4.1 Tool Life Model

The experiments were carried out on a complex machine tool and disc tools rotated 50 degree around y-axis, as shown in Figure 1. The material of blisk is TC17 titanium alloy. The failure criterion of tool is that the average abrasion of the flank face reaches 0.3 mm or the maximum reaches 0.6 mm. The processing parameters of experiments are listed in Table 1.

![Figure 1. Cutting process for disc milling cutter](image)

| Spindle Speed \( v \)(m/min) | Feed Speed \( f \)(mm/tooth) | Cutting Depth \( d \)(mm) | Tool life \( T \)(min) |
|-----------------------------|-----------------------------|--------------------------|----------------------|
| 105                         | 0.038                       | 15                       | 38.06                |
| 105                         | 0.028                       | 15                       | 43.33                |
| 105                         | 0.0192                      | 15                       | 58.42                |
| 92                          | 0.044                       | 15                       | 32.54                |
| 92                          | 0.033                       | 15                       | 40.78                |
| 92                          | 0.022                       | 15                       | 52.50                |
| 79                          | 0.051                       | 15                       | 25.76                |
| 79                          | 0.038                       | 15                       | 33.33                |
| 79                          | 0.026                       | 15                       | 40.58                |

MCMC is used to get parameters of the likelihood function for the tool life function. The
parameters that been used as shown in the following:

\[ \lambda \sim \text{Gamma}(0,100), \quad \beta \sim \text{Uniform}(0,1.5) \]
\[ r_1 \sim \text{Normal}(0,0.01), \quad r_2 \sim \text{Normal}(0,0.01) \]
\[ r_3 \sim \text{Normal}(0,0.01) \]

(18)

Posterior distributions of the above parameters are estimated using Openbugs. The initial values of the Markov chain were set as \( \lambda = 1, \beta = 1 \), and the initial values of \( r_1, r_2, r_3 \) were automatically generated. The estimated parameters are listed in Table 2 (After 200,000 iterations of convergence) and the parameter iteration trajectory map is shown in figure 2.

Based on Equation. (2) – equation (9), the average lifetime of turbine disc milling cutting tool (TC17 titanium alloy) can be calculated as shown in equation. (19) – equation (21).

\[
E(t) = \int_0^\infty t f(t) dt = \int_0^\infty R(t) dt
\]

Let \( l = \lambda t^\beta \exp Z \), then \( dt = \frac{t^{(\beta-1)}}{\beta (\lambda \exp Z)^{\beta}} dl \), hence:

\[
E(t) = \int_0^\infty t f(t) dt = \int_0^\infty R(t) dt = \frac{1}{\beta} (\lambda \exp Z)^{-1/\beta} \Gamma(1/\beta) \Gamma(1+1/\beta)
\]

(20)

According to the posterior estimation of the parameters in Table 2, the average tool life can be obtained as:

\[
E(t) = 37.66 \times (v^{1.05144} d^{-0.01876}) (t^{0.05144})
\]

(21)

4.2 Experiment Design

The cutting force signal can be amplified by Kistler 5080. The A/D acquisition card (PCIM-DAS1602/16, Kistler) was implemented into the computer. Table 3 demonstrates the cutting parameters. 35 groups of experiment were carried out and the average tool life was obtained by equation. (3). The material removal rate can be calculated:

\[
Q = \frac{1000bfNVD_t}{60\pi D}
\]

(22)

Where, \( b \) is the cutting width, \( v \) represents cutting speed, \( f_c \) is the feed per tooth, \( d \) is the cutting depth, \( N_t \) is the number of disc milling cutting tools, \( D \) denotes the diameter of the disc milling cutting tool.

| Table 2 The parameters estimated by MCMC. |
|----------------|----------------|----------------|----------------|----------------|
| Parameter | Mean | Standard Deviation | Median | Simulation Error | Lower Confidence Interval | Upper confidence interval |
| \( \lambda \) | 0.006 | 0.01 | 0.005 | 2.103E-5 | 0.002 | 0.01383 |
| \( \beta \) | 1.392 | 0.09 | 1.418 | 6.582E-4 | 1.147 | 1.497 |
| \( r_1 \) | -0.004 | 10.01 | 0.003 | 0.03243 | -19.6 | 19.63 |
| \( r_2 \) | -0.051 | 10.06 | -0.038 | 0.03069 | -19.87 | 19.71 |
| \( r_3 \) | 0.019 | 9.98 | 0.002 | 0.03332 | -19.68 | 19.54 |
Figure 2. Iteration map.

Table 3  Experimental parameters.

| Number of groups | \( v \) (m/min) | \( f \) (mm/tooth) | \( d \) (mm) | \( F \) (N) | \( Q \) (mm³/s) | Life expectancy /\( E(t) \) |
|------------------|----------------|-------------------|-------------|-----------|---------------|-----------------|
| 1                | 30             | 0.02              | 28          | 1148.6    | 49.7          | 45.05           |
| 2                | 30             | 0.035             | 33          | 1366.8    | 102.5         | 44.23           |
| 3                | 30             | 0.05              | 38          | 1718.7    | 168.62        | 43.73           |
| 4                | 30             | 0.065             | 43          | 1858.6    | 248           | 43.38           |
| 5                | 30             | 0.08              | 48          | 2299.7    | 340.7         | 43.11           |
| 6                | 40             | 0.02              | 33          | 1117.4    | 78.1          | 45.11           |
| 7                | 40             | 0.035             | 38          | 1287.5    | 157.3         | 44.27           |
| 8                | 40             | 0.05              | 43          | 1662.9    | 254.3         | 43.77           |
| 9                | 40             | 0.065             | 48          | 1877.3    | 369.1         | 43.41           |
| 10               | 40             | 0.08              | 28          | 2208.4    | 265           | 42.76           |
| 11               | 50             | 0.02              | 38          | 1154.3    | 112.4         | 45.17           |
| 12               | 50             | 0.035             | 43          | 1548.5    | 222.5         | 44.32           |
| 13               | 50             | 0.05              | 48          | 1644.8    | 354.9         | 43.80           |
| 14               | 50             | 0.065             | 28          | 1815.7    | 269.1         | 43.06           |
4.3. Gray Correlation Grade Calculation
The study is to find the optimal cutting speed, feeding rate per tooth, and cutting depth. Based on equation (10) and equation (11), the normalized data were listed in Table 4. According to equation (12) and equation (14), the gray correlation coefficients of cutting force $\Delta (F)$, material removal $\Delta (Q)$, sequence differences of cutting force and material removal rate $\gamma_o (F)$ and $\gamma_o (Q)$, the GRG of cutting force to the material removal rate $\gamma$ are given in Table 5.

Table 4 Normalized data.

| Number of groups | $v$ (m/min) | $f$ (mm/tooth) | D (mm) | F(N) | Q (mm$^3$/s) |
|------------------|-------------|---------------|--------|------|--------------|
| 1                | 0           | 0             | 0      | 0.9736 | 0           |
| 2                | 0           | 0.25          | 0.25   | 0.7890 | 0.0797      |
| 3                | 0           | 0.5           | 0.5    | 0.4914 | 0.1795      |
| 4                | 0           | 0.75          | 0.75   | 0.3730 | 0.2994      |
| 5                | 0           | 1             | 1      | 0     | 0.4393      |
| 6                | 0.25        | 0             | 0.25   | 1     | 0.0429      |
| 7                | 0.25        | 0.25          | 0.25   | 0.8561 | 0.1624      |
| 8                | 0.25        | 0.5           | 0.5    | 0.5386 | 0.3089      |
| 9                | 0.25        | 0.75          | 1      | 0.3572 | 0.4822      |
| 10               | 0.25        | 1             | 0      | 0.0772 | 0.3250      |
| 11               | 0.5         | 0             | 0.5    | 0.9687 | 0.0947      |
| 12               | 0.5         | 0.25          | 0.75   | 0.6353 | 0.2609      |
| 13               | 0.5         | 0.5           | 1      | 0.5539 | 0.4607      |
| 14               | 0.5         | 0.75          | 0      | 0.4093 | 0.3312      |
| NO | F(N) | Q | 0.25 | 0.0125 | 0.5143 |
|----|------|---|------|--------|--------|
| 15 | 0.5  | 1 | 0.25 | 0.0125 | 0.5143 |
| 16 | 0.75 | 0 | 0.75 | 0.9645 | 0.1553 |
| 17 | 0.75 | 0.25 | 1 | 0.6028 | 0.375  |
| 18 | 0.75 | 0.5 | 0 | 0.5057 | 0.2999 |
| 19 | 0.75 | 0.75 | 0.25 | 0.1525 | 0.4995 |
| 20 | 0.75 | 1 | 0.5 | 0.0388 | 0.7392 |
| 21 | 1 | 0 | 1 | 0.7475 | 0.2249 |
| 22 | 1 | 0.25 | 0 | 0.661 | 0.2312 |
| 23 | 1 | 0.5 | 0.25 | 0.5114 | 0.5187 |
| 24 | 1 | 0.75 | 0.5 | 0.3980 | 0.6968 |
| 25 | 1 | 1 | 0.75 | 0.0537 | 1 |
| 26 | 0 | 0.5 | 0.5 | 0.9610 | 0.1795 |
| 27 | 0.5 | 0.5 | 0 | 0.5281 | 0.2374 |
| 28 | 0.5 | 0.5 | 1 | 0.4544 | 0.4607 |
| 29 | 0.25 | 0.5 | 0.5 | 0.5425 | 0.2643 |
| 30 | 0.75 | 0.5 | 0.5 | 0.4761 | 0.4338 |
| 31 | 0.5 | 0.75 | 0.5 | 0.3350 | 0.4762 |
| 32 | 0.5 | 0.25 | 0.5 | 0.6030 | 0.2219 |
| 33 | 0.5 | 0.5 | 0.25 | 0.5164 | 0.2933 |
| 34 | 1 | 0.5 | 0.5 | 0.4015 | 0.5187 |
| 35 | 0.5 | 0.5 | 0.5 | 0.5183 | 0.3490 |

Table 5 Processing data.

| NO | F(N) | Q | 0.25 | 0.0125 | 0.5143 |
|----|------|---|------|--------|--------|
| 1  | 0.9736 | 0.0000 | 0.0264 | 1.0000 | 0.9499 | 0.3333 | 0.6416 |
| 2  | 0.7891 | 0.0797 | 0.2109 | 0.9203 | 0.7033 | 0.3520 | 0.5277 |
| 3  | 0.4914 | 0.1795 | 0.5086 | 0.8205 | 0.4957 | 0.3787 | 0.4372 |
| 4  | 0.3731 | 0.2994 | 0.6269 | 0.7006 | 0.4437 | 0.4164 | 0.4301 |
| 5  | 0.0000 | 0.4393 | 1.0000 | 0.5607 | 0.3333 | 0.4714 | 0.4024 |
| 6  | 1.0000 | 0.0429 | 0.0000 | 0.9571 | 1.0000 | 0.3431 | 0.6716 |
| 7  | 0.8561 | 0.1624 | 0.1439 | 0.8376 | 0.7766 | 0.3738 | 0.5752 |
| 8  | 0.5386 | 0.3089 | 0.4614 | 0.6911 | 0.5201 | 0.4198 | 0.4699 |
| 9  | 0.3573 | 0.4822 | 0.6427 | 0.5178 | 0.4375 | 0.4912 | 0.4644 |
| 10 | 0.0772 | 0.3250 | 0.9228 | 0.6750 | 0.3514 | 0.4255 | 0.3885 |
| 11 | 0.9688 | 0.0947 | 0.0312 | 0.9053 | 0.9412 | 0.3558 | 0.6485 |
| 12 | 0.6354 | 0.2609 | 0.3646 | 0.7391 | 0.5783 | 0.4035 | 0.4909 |
| 13 | 0.5539 | 0.4607 | 0.4461 | 0.5393 | 0.5285 | 0.4811 | 0.5048 |
| 14 | 0.4094 | 0.3312 | 0.5906 | 0.6688 | 0.4585 | 0.4278 | 0.4431 |
| 15 | 0.0125 | 0.5143 | 0.9875 | 0.4857 | 0.3361 | 0.5073 | 0.4217 |
| 16 | 0.9646 | 0.1553 | 0.0354 | 0.8447 | 0.9338 | 0.3718 | 0.6528 |
| 17 | 0.6029 | 0.3750 | 0.3971 | 0.6250 | 0.5573 | 0.4444 | 0.5009 |
| 18 | 0.5058 | 0.3000 | 0.4942 | 0.7000 | 0.5029 | 0.4167 | 0.4598 |
| 19 | 0.1526 | 0.4995 | 0.8474 | 0.5005 | 0.3711 | 0.4998 | 0.4354 |
| 20 | 0.0388 | 0.7393 | 0.9612 | 0.2607 | 0.3422 | 0.6573 | 0.4997 |
| 21 | 0.7475 | 0.2249 | 0.2525 | 0.7751 | 0.6645 | 0.3921 | 0.5283 |
| 22 | 0.6610 | 0.2313 | 0.3390 | 0.7687 | 0.5959 | 0.3941 | 0.4950 |
As seen in Table 5, the maximum value of gray correlation 0.6729 with cutting speed 70m/min, the feeding rate per tooth 0.08, the cutting depth 43mm. The minimum GRG is 0.3884 with the cutting parameter 40m/min, the feeding rate per tooth 0.08 and the cutting depth 28mm. Data in table 5 is calculated using the formula obtained in the discrete domain rather than the continuous domain as a consequence, those data cannot represent all cutting parameter combinations. Therefore, the RBF neural network and PSO algorithm are applied to predict the GRG in follow.

4.4. RBF Neural Network

To extend the grey relational grade (GRG) to the continuous domain, a radial basis neural network was established. Based on the assumption that global error is 0.001, the dispersion rate is 2, the cutting parameters and the corresponding grey relational grade (GRG) in the first 30 groups are used to train the network. To obtain the network prediction effect map and error map, the cutting parameters and the corresponding grey relational grade (GRG) in the last 5 groups are used to test the network as shown in figure. 3 and figure. 4.

Figure 3. RBF neural network prediction.
Figure 4. Prediction error of RBF neural network.

As shown in figure. 3 and figure. 4, 26th experiment held the maximum prediction error with 20.01% in training group and 34th experiment had the maximum prediction error with 8.27%. It is shown that using the RBF neural network can more accurately predict the value of GRG.

4.5. Optimal GRG

The particle swarm optimization algorithm was used to optimize GRG and RBF neural network was established to find the best cutting parameters. The optimization goals and corresponding constraints are as follows:

\[
\begin{align*}
\text{Find} & : X = (v, f, d) \\
\text{Max} & : \text{GRG} = \text{RBF}(X) \\
\text{s.t.} & : \\
& 30 \text{ m/min} \leq v \leq 70 \text{ m/min} \\
& 0.02 \text{ mm/tooth} \leq f \leq 0.08 \text{ mm/tooth} \\
& 28\text{mm} \leq d \leq 48\text{mm} \\
& E(t) \geq 43\text{min}
\end{align*}
\]

This paper uses a radial basis neural network and particle swarm optimization algorithm to extend the GRG calculated to the continuous domain. Specifically, the average tool life is used as a constraint to optimize the processing parameters considering the tool life and reliability factors. Table 2 shows that there are 4 groups whose average tool life less than 43 min. The optimized objective function is the GRG value predicted by the RBF neural network. The ranges of the parameters are given in equation 23.

PSO algorithm is used to find the optimal GRG. First, learning rate \( c_1, c_2 \) were set to 2, weights of \( \omega \) was set as 0.95, the initial size of particles was 30, the maximum number of iterations for the algorithm is 100. The maximum GRG value obtained by the particle swarm optimization algorithm is 0.6785. Corresponding processing parameters were \( v = 70 \text{ m/min} \), \( f = 0.075 \text{ mm/tooth} \), \( d = 43\text{mm} \) and the average tool life 43.83 min. The maximum GRG value obtained by the GRA method is slightly greater than the GRG-RBF-PSO method, the average life of the cutting tool is shorter than 43 min. Therefore, the proposed method can achieve the maximum GRG value in continuous domain and achieve a higher average tool life.

5. Experimental verification

The last stage in this work is to confirm the validity of the optimal results through experiments. The optimal results of the proposed approach need to be verified. To verify the advantage of the proposed approach, two groups of experiments were carried out. Experimental parameters of the first group was set of \( V = 66 \text{ m/min} \), and \( f = 0.075 \text{ mm/tooth} \) and \( d_e = 43 \text{ mm} \) (the optimized results of the proposed approach were used). The experimental results are shown in Table 3. The data from the experiments indicates that the proposed method can achieve the maximum GRG value in continuous domain and achieve a higher average tool life.
approach). Experimental parameters of the second group was set of $V=70 \text{ m/min}$, and $f_c=0.075 \text{ mm/tooth}$ and $d_w=43 \text{ mm}$ (the optimized results of only used GRA-RBF-PSO approach). Each group of experiment was repeated three times. The results are listed in Table 6. The results of the first group was that cutting force, MRR and the average tool life were found to be 2004.6 N, 702.63 mm$^3$/s and 43.83 min. The results of second group was that cutting force, MRR and the average tool life were found to be 1765.0 N, 667.25 mm$^3$/s and 42.94 min. The performance of the first group of experiments was compared with the second group, where cutting force, MRR, GRG decreased 11.92%, 5.07% and 2.03% and the average and the actual tool life extended 2.03% and 7.35%. It can be seen that the performance of the optimal results of the proposed approach was better than only used GRA-RBF-PSO approach.

### Table 6 The results of verified experiments.

|                | GRA-RBF-PSO | GRA-RBF-PSO of Reliability-based Improvement rate (%) |
|----------------|-------------|-----------------------------------------------------|-------------------------------------------------|
|                | $V=66 \text{ m/min}$ | $f_c=0.075 \text{ mm/tooth}$ | $d_w=43 \text{ mm}$ | $V=70 \text{ m/min}$ | $f_c=0.075 \text{ mm/tooth}$ | $d_w=43 \text{ mm}$ |
| F              | 2004.6      | 1765.0      | -11.92   |
| Q              | 702.63      | 667.25      | -5.07    |
| GRG            | 0.6861      | 0.6785      | -1.1     |
| Average tool life | 42.94       | 43.83       | 2.03     |
| Actual tool life | 64.76       | 69.52       | 7.35     |

6. Conclusion
The average tool life is calculated by combining Weibull distribution with proportional hazard model, which reflects the tool reliability and tool life. It is necessary to consider the influence of the average tool life in optimization machining parameters. In the paper, the average tool life is taken as the constraint and a multi-objective optimization approach GRA-RBF-PSO is applied to solve the problem of process parameters optimization for disc milling TC17 blisk-tunnels. Conclusions are drawn as below:

(1) Taking the average tool life as the constraint compared to without taking that, optimization results can decrease cutting force and extend the average tool life and tool reliability without losing MRR.

(2) The optimal parameters combination is cutting speed of 70 m/min, feed rate per tooth of 0.075 mm/tooth and cutting depth of 43 mm.

(3) The results of the proposed approach are more science and reasonable, which can be applied to process blisk.

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