Multi-objective Optimization of Turning Tool Geometric Parameters Based on Kriging Model

Jianxiang Sun, Huan Xie, Wei Zeng, Yaoyao Tong, Zhenyu Cai

1 Xijing University, Xi’an, Shaan Xi, China
2 Xi’an Shiyou University, Xi’an, Shaan Xi, China
3 Changchun Automobile Industry Institute, Changchun, Jilin, China
4 Shanghai Academy of Spaceflight Technology, Shanghai, China
5 email:s980322@outlook.com

Abstract: Cutting performance parameters of turning tool in different geometric parameters are obtained using finite element model, and the Kriging models of cutting stress and temperature are constructed, taking the cutting performance parameters as training samples. The multi-objective optimization model of turning tool geometric parameters is established based on the constructed cutting performance Kriging models, in which the design variables are rake angle, relief angle and cutting-edge radius, the objective parameters are cutting stress and temperature. The multi-island genetic algorithm is used to obtain the optimum turning tool geometric parameters: rake angle $\gamma_0$ is 10.59°, relief angle $\lambda_s$ is 6.15° and cutting-edge radius $\gamma_e$ is 0.73mm. The simulation results after optimization demonstrate that the corresponding cutting temperature reduces 263.1°C, cutting stress drops by 550.8MPa.

1. Introductions

The geometric parameters of the turning tool directly affect the processing quality, accuracy and efficiency. Optimizing the turning tool geometric parameters can ensure the processing quality and improve the turning efficiency. Researchers have carried out a lot of work on the optimization of the tool geometric parameters. Wu et al. took the high-hard cutting processes in different application occasions as objects, and the statistical analysis method is adopted to obtain the optimal tool geometric parameter value range, which can provide reference for cutting process optimization. Zeng et al. obtained optimized geometrical parameters of turning tools by combining the orthogonal test method and finite element simulation. Wu and Hu took the geometric parameters of the boring cutter as the object, and the optimization model of the tool's geometric parameters is established, then the optimized geometric parameters of the boring cutter under given cutting conditions were obtained by using the constraint optimization function of the ANSYS software. Cheng et al. took the turning of nickel-based superalloy Inconel718 as an example, calculating the tool stress and cutting temperature under different tool geometric parameters by using finite element numerical simulation, and the optimized tool geometric parameters were obtained through comparative analysis. Subramanian et al. obtained the optimized tool geometry parameters through specific experimental tests by combining the statistical analysis method and the response surface model. Lungu et al. optimized the geometric parameters of turning tools by Tiankou robust optimization design method considering the influences of machining noise factors on the cutting quality.
2. Finite element model of tool cutting performance

2.1 Turning tool geometric parameters and turning performance indicators

Taking the turning of 45 steel with a cemented carbide tool as an example, the preferred geometric parameters of the turning tool are rake angle $\gamma_r=10^\circ$, relief angle $\lambda_s=6^\circ$, cutting-edge radius $r_e=0.55\text{mm}$, turning tool main deviation angle $K_r=90^\circ$. The cutting process parameters are: cutting speed $v=5\text{m/s}$, feed amount $f=0.3\text{mm/r}$, back cutting amount $a_b=2\text{mm}$. Among them, the tool geometric parameters that affect the cutting performance of the turning tool are mainly the rake angle $\gamma_r$, the relief angle $\lambda_s$ and the cutting-edge radius $r_e$\[^5\]. Therefore, this paper chooses the rake angle $\gamma_r$, the relief angle $\lambda_s$, and the tool tip arc radius $r_e$ as the optimal design variables.

Normally, large stress will be formed at the cutting position and large amount of heat is also generated during the turning process. In order to ensure the cutting quality of the work piece and prolong the service life of the tool, the cutting stress and the cutting heat are required to be as low as possible. Therefore, this paper regards the cutting stress $\sigma$ and the cutting temperature $T$ as the cutting performance optimization indexes.

2.2 Finite element model

To calculate the cutting performance of the turning tool under different tool geometric parameters, a three-dimensional finite element model of a certain type of tool is constructed in ABAQUS software, then the tool and workpiece model are meshed using the 8-node element C3D8RT. The elastic modulus of the work piece is 201GPa, the Poisson's ratio is 0.3.

In order to simulate the cutting properties such as temperature and stress in the material cutting progress, Johnson-Cook material constitutive model is used to define the workpiece material, and it's basic form\[^9\] is showed in equation(1).

$$ \sigma = [A + B \varepsilon^*] [1 + C \ln \varepsilon^*] [1 - \left( \frac{T - T_r}{T_m - T_r} \right)^m], \quad (1) $$

Among them, $A$, $B$, $n$, $C$, $m$ are material parameters, which respectively represent the yield limit, hardening modulus, hardening coefficient, strain sensitivity index, and thermal softening coefficient of the material; $\varepsilon^*$ is the equivalent plastic strain rate, and $T_r$ represents the room temperature (20°C), $T_m$ represents the melting temperature (1480°C). The specific values are showed in table 1.

| Table 1. Johnson-Cook Model parameters |
|----------------------------------------|
| $A$ (MPa) | $B$ (MPa) | $C$ | $n$ | $m$ |
| 795       | 512       | 0.023 | 0.26 | 1.02 |

To simulate the generation process of chips in the turning process, the equation (2) is used to describe it.

$$ D = \sum \frac{\Delta \varepsilon}{\varepsilon^*}, \quad (2) $$

where, $\varepsilon_f$ represents the critical strain when the material fails; $\Delta \varepsilon$ represents the cumulative failure strain; when $D=1$, the material breaks, and chips are generated. When using the cutting parameters illustrated in section 1.1, at a certain time step, the results of the turning performance analysis are showed in figure 1.
3. Kriging model of the turning tool performance

The Kriging model belongs to an unbiased estimation model with the smallest estimated variance [8], which can analyze the correlation between sample data, obtain the trend and dynamics of the sample. It has the advantages of fitting the nonlinear relationship between the variable and the response. The specific form of the Kriging model could be found in the reference [8]. In order to build the Kriging model a turning tool cutting performance, the turning tool the rake angle $\gamma_o$, the relief angle $\lambda_s$ and cutting-edge radius $\gamma_e$ are used as the design variables, and the cutting stress $\sigma$ and cutting temperature $T$ are used as response values, and the corresponding finite element simulation is used to obtain the corresponding training samples. The number of training samples of the Kriging model is $m=3k$, where $k=(n+1)(n+2)/2$, and $n$ is the number of design variables. In this research, the number of training sample points is 30 as the number of design variables is 3.

Taking the design variable value determined in Section 1.1 as the center, floating up and down by 50%, the value intervals of the training samples are determined: the rake angle $\gamma_o \in [5, 15]$, the relief angle $\lambda_s \in [3, 9]$, the cutting-edge radius $\gamma_e \in [0.275, 0.825]$. The Latin hypercube experimental design method [10] is used to sample 30 sets of design variable values from the variable value intervals, and the cutting performance finite element model constructed in Section 1 is used to simulate the geometric parameters of different turning tools. The corresponding cutting performance index is shown in table 2, and it is used as the training sample of the cutting performance Kriging model. According to the training samples of the Kriging model in table 2, calculating the correlation matrix $R$ and the unit column vector $f$ respectively, and the cutting stress $\sigma$ and cutting temperature $T$ Kriging model regression coefficients $\hat{\beta}$ are calculated by using the least square method.

$$\hat{\beta}_\sigma = (f^TR^{-1}y)^{-1}f^TR^{-1}y = -0.017, \quad (3)$$

$$\hat{\beta}_T = (f^TR^{-1}y)^{-1}f^TR^{-1}y = -0.126. \quad (4)$$

The maximum likelihood estimation method is used to calculate the relevant parameters $\theta_k$, and the Kriging model parameters of the cutting stress and cutting temperature are obtained $\theta_{\sigma}=0.021$, $\theta_{T}=0.391$. Then, the correlation vector between the predicted point $x$ and the sample data $r^T(x)$ can be calculated, and the response value can be obtained, that is, the Kriging model of cutting stress and cutting temperature are constructed.

| Number | $\gamma_o$ (°) | $\lambda_s$ (°) | $\gamma_e$ (mm) | $\sigma$ (MPa) | $T$ (MPa) |
|--------|----------------|----------------|-----------------|---------------|-----------|
| 1      | 11.48509       | 3.78153        | 0.485974        | 1781.732      | 755.0984  |
| 2      | 12.4509        | 8.398436       | 0.445596        | 1676.674      | 806.7131  |
| 3      | 10.48537       | 4.915378       | 0.807167        | 1974.481      | 828.6852  |
| ...    | ...            | ...            | ...             | ...           | ...       |
| 29     | 8.752914       | 3.966759       | 0.653287        | 1761.613      | 739.3755  |
| 30     | 10.82665       | 4.075501       | 0.425209        | 1755.149      | 733.3291  |

Table 2. Training samples of Kriging models
To ensure the prediction accuracy of the established Kriging models, the root mean square error [8] is used to evaluate the prediction accuracy. And the root mean square error (RMSE) of Kriging model prediction points is:

$$RMSE = \sqrt{E[(\hat{y}(x) - y(x))^2]} = \sqrt{\sigma^2 + \mu^T (f^T R^{-1} f)^{-1} \mu - \mu^T r^T R^{-1} r}.$$  (5)

In the error test process, 10 groups of cutting performance indicators are randomly selected as the error test samples in table 2, compared it with the cutting performance indicators predicted by the Kriging models, then the RMSE value of the $\sigma$ and the $T$ are obtained, and the specific values are 0.0671 and 0.0981, respectively. The results indicate that the established Kriging model has a small fitting error and meets the requirements of prediction accuracy.

4. Optimization of turning tool geometric parameters based on Kriging model

4.1 Optimization Design Model of Turning Tool Geometry Parameters

Regarding the rank angle $\gamma_o$, the relief angle $\lambda_s$ and the cutting-edge radius $\gamma_e$ as design variables, taking the cutting stress $\sigma$ and the cutting temperature $T$ as cutting performance optimization indexes, and using the established cutting performance Kriging model as the objective function, the optimization design model of turning tool geometric parameters is established in equation (6).

$$\text{find: } \gamma_o, \lambda_s, \gamma_e$$

$$\text{min: } \sigma(X) = f(X)^T \hat{\beta}_o + r^T(X) R^{-1}(y - F\hat{\beta}_o)$$

$$\text{min: } T(X) = f(X)^T \hat{\beta}_r + r^T(X) R^{-1}(y - F\hat{\beta}_r),$$

$$\text{s.t.}$$

$$-9 < \gamma_o < -3, -9 < \lambda_s < -3, 0.6 < \lambda_e < 1.8$$

$$\sigma \geq 0, T \geq 0$$

where, $X$ is the design variable, $\gamma_o$, $\lambda_s$, $\gamma_e$, $\sigma(X)$ and $T(X)$ are the cutting stress $\sigma$ and the cutting temperature $T$ Kriging model respectively.

4.2 Multi-objective Optimization Calculation of Turning Tool Geometric Parameters

To obtain the globally optimal tool geometric parameters, the multi-island genetic algorithm[11] is used to solve the optimization model, and the optimization process is shown in figure 2. Finally, the final optimization results of cutting stress $\sigma$ and cutting temperature $T$ are obtained after 1000 interpolations, and the specific values are 1133.4MP and 728.9℃, respectively. Currently, the corresponding tool geometric parameters are rake angle $\gamma_o=10.59^\circ$, relief angle $\lambda_s=6.15^\circ$, and cutting-edge radius $\gamma_e=0.73\text{mm}$. Then, the optimized tool geometric parameters were substituted into the finite element analysis model of cutting performance, and the analysis results of turning performance were obtained as shown in figure 3. The cutting temperature and cutting stress values were 522.1℃ and 748.2MPa respectively. The cutting temperature decreases by 263.1℃ and the cutting stress decreases by 550.8 MPa compared with the corresponding values showed in figure 2. The results verify the effectiveness of the proposed method.
5. Conclusions
Taking the 45 steel cutting process with the cemented carbide turning tool as the object, a multi-objective optimization model of tool geometric parameters was established based on the Kriging model of tool cutting performance, and the optimized tool geometric parameters were obtained by using the multi-island genetic algorithm: the rake angle is 10.59°, the relief angle is 6.15°, and the cutting-edge radius is 0.73mm. The cutting stress and cutting temperature are obviously reduced after optimization. It is beneficial to ensure the cutting quality and prolong the service life of turning tools.

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