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Multi-objective Optimization of Machined Surface Integrity for Hard Turning Process

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Abstract

Hard turning has characteristics of good processing flexibility and environmental performance. Under certain processing conditions it has more advantages than grinding process. Also, it has become the new process which has broad prospects for development. After process of hard cutting, the integrity of machined surface plays a vital role for performance of the workpiece. In this paper, the integrity of machined surface (surface roughness and the thickness of the plastic deformation) is focused on for hard turning process of die steel Cr12MoV. The multi-objective optimization was adopted. On the basis of revealing the relationship between cutting conditions and surface integrity indicators, combined with response surface methodology (RSM) the correspondence between the surface integrity evaluation and cutting parameters is established. By improved particle swarm algorithm a multi-objective optimization of surface integrity prediction was achieved, and the relative optimal cutting parameters were obtained. The research results of this paper provide the theoretical basis and reference for optimization of the experimental conditions.

***Keywords**: Hard Cutting, Die steel Cr12MoV, Machined surface integrity, Multi-objective optimization*

1. Introduction

As finishing process, the hard machining processing technology has good flexibility and environmental performance. Hard turning process can replace of grinding process under certain processing conditions partially[1].In order to get better performance for the workpiece. It is necessary to study the impact mechanism of cutting conditions to surface integrity for the workpiece to play a better role. For hard cutting process, the surface integrity including roughness, surface residual stress, hardening layer and other indicators[2].But for many application conditions the merits of surface integrity are influenced by a number of indicators, so it is necessary to expand the research to multi-objective optimization of surface integrity.

Tuğrul Özel *et al*. used the response surface methodology (RSM) to establish a surface roughness prediction models in the process of ball tool milling titanium, and the research obtained optimized cutting conditions. This method based on statistics and has a high accuracy[3].Sharma and others take the three elements as the input variable, take the roughness as the output variable to established a neural network prediction model for surface roughness[4].Hamdi *et al*. studied the impact of CBN flank wear on surface roughness, and they established a prediction model of the surface roughness by using cutting three elements and the tool wear as input [5]. Hamdi *et al*. used SVM to establish a predictive model of surface roughness based on vector machine and compared with

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surface roughness neural network predictive model and they found that the accuracy of prediction model based on vector machine was higher than neural network model [6]. By combining experimental observation and finite element analysis method, Han used heat (workpiece surface temperature), force (unit cutting force increment) as a criterion the white layer formation to establish the prediction model for determining the existence of the white layer in the right angle cutting process [7].

In multi-objective optimization algorithm programed, there may be no contradictory absolute optimal solution between the various objectives, so optimal synthesis of many factors must be weighed before. Under different conditions relative optimization of cutting parameters could be obtained. By using improved particle swarm optimization algorithm for surface roughness and multi-objective optimization of harden layer thickness. The results in this paper provided a basis for optimization of cutting conditions.

2. Analysis of Machined Surface Integrity for Hard Cutting Process

If the rotating bending fatigue strength was used as the typical index for workpiece performance, surface roughness and surface plastic degenerating layer thickness are have significant effect on strength of the surface roughness. In process of fatigue damage, the surface is generally crack in initiation position. The greater the surface roughness, the deeper the surface grooves, the smaller the grain bottom radius. The stress caused by processing grain trenches will be more focused on. The crack will be easier to spread along the interior of the workpiece at that point, so the fatigue properties of the workpiece will be worse [8].

In the process of high-strength steel, the plastic deformation of the processed surface will lead to surface fibrosis, grains broken, the yield strength of the material improved, ductility and toughness reduced, hardness increased, the lattice distortion, dislocation activity due to dislocation pile weakened. Under alternating stress, plastic deformation of the surface layer will prevent dislocation lines extending into the surface, thus postponing the fatigue cracks. Therefore increases of thickness of plastic deformation will improve the fatigue life of workpiece.

Two indicators mentioned above restrict and influence each other, in order to improve the rotary bending fatigue life of workpiece, and control strategy of cutting conditions are often contradictory. Multi-objective optimization strategies are effective methods to solve this problem. If the bending fatigue strength of the workpiece was used as the ultimate measure, surface roughness and affected layer thickness can be as multi-objective optimization of intermediate variables. Due to tool wear have an obvious effect on machined surface structure formation. The tool wear and cutting speed, feed and cutting depth are selected as the four input variables. The boundary of condition for this model is shown in equation (1):

$$\begin{cases} \min SR(VB, n, f, a_p) \\ \max MLT(VB, n, f, a_p) \end{cases} \quad \text{and} \quad \begin{cases} VB_{\min} \le VB \le VB_{\max} \\ n_{\min} \le n \le n_{\max} \\ f_{\min} \le f \le f_{\max} \\ a_{p\min} \le a_p \le a_{p\max} \end{cases} \tag{1}$$

Here, SR is surface roughness, MLT is metamorphic layer thickness. n is spindle speed, f is feed rate, ap is depth of cut, and VB is flank wear of cutting tool. In order to establish the relationship between cutting parameters and objectives optimization, cutting parameters and mapping of surface integrity parameters are established by response surface method. With maximum fatigue life for the purpose of optimizing and particle swarm optimization is used to improve algorithm for modeling and analysis. The hierarchical result sequence of model is shown in Figure 1.

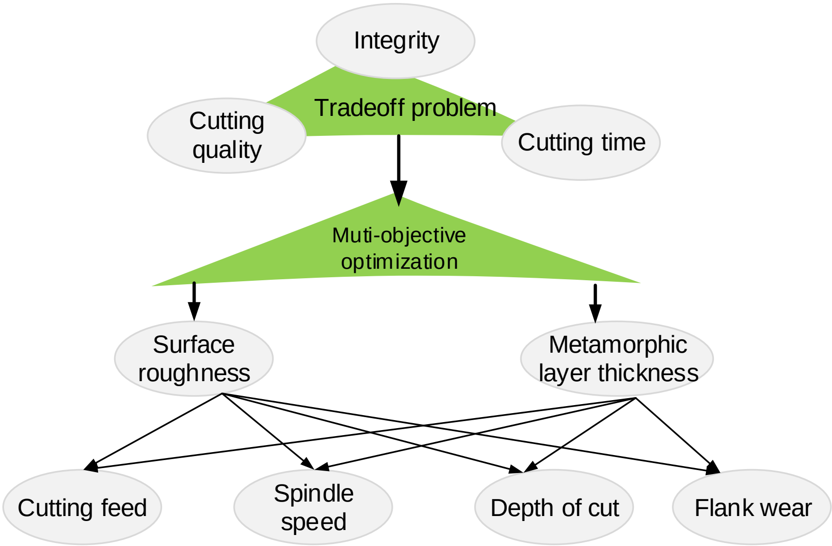

Figure 1. Hierarchy Diagram of Multi-Objective Optimization

3. Experiment Setting Up

In this study PCBN tool is used as the test tool, and the tool is produced by Zhuzhou cemented carbide cutting tools company, whose model is MVJNR2020K16. The material of rotating bending fatigue specimens is Cr12MoV, and the test specimens with a circular cross-section. The middle section diameter is 7.5mm, and the turning field is shown in Figure 2. The PQ-6 bending fatigue testing machine is used as the fatigue life test equipment. The conditions of machine control and measurement system meet the requirements of GB/T4337-2008. The rotating bending fatigue test site is shown in Figure 3.

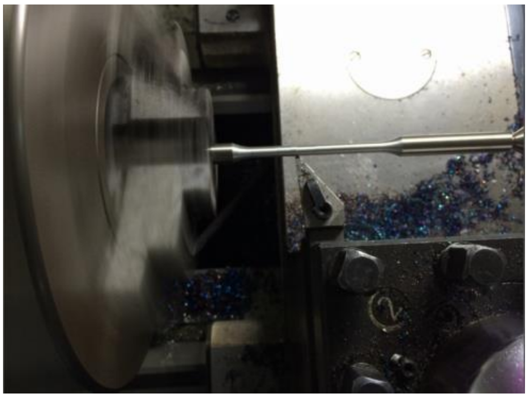

Figure 2. Turning Site for Fatigue Specimen

Figure 3. Fatigue Test of Rotating Bending

To obtain the mapping relationship between surface integrity and cutting parameters, the rotating bending fatigue test adopted L16 orthogonal experiments in this paper. The test design and test are shown in Table 1:

Table 1. Results of Orthogonal Experiments

Serial number	n (r/min)	f (mm/r)	a_p (mm)	V_B (mm)	SR (μm)	MLT (μm)
1	640	0.08	0.05	0.03	1.272	11.3
2	640	0.10	0.10	0.12	0.907	10.0
3	640	0.15	0.15	0.22	1.274	13.4
4	640	0.20	0.20	0.30	1.352	15.0
5	725	0.08	0.10	0.22	1.680	16.7
6	725	0.10	0.05	0.30	1.944	13.2
7	725	0.15	0.20	0.03	0.964	9.60
8	725	0.20	0.15	0.12	1.047	7.80
9	810	0.08	0.15	0.30	0.685	13.1
10	810	0.10	0.20	0.22	1.065	11.0
11	810	0.15	0.05	0.12	1.863	7.00
12	810	0.20	0.10	0.03	0.896	8.50
13	896	0.08	0.20	0.12	0.424	5.00
14	896	0.10	0.15	0.03	2.067	10.6
15	896	0.15	0.10	0.30	0.710	17.2
16	896	0.20	0.05	0.22	1.618	7.70

4. Establishment of Surface Integrity Forecasting Model

Normally, in the independent variable space of some relatively area is small. The relationship between the input and the response can be approximately represented by low order polynomial. The equation (2), equation (3) and equation (4) are the first order, the first order interaction and the two order interaction for the response surface method model. β is all kinds of coefficient, K is the number of independent variables, and ε is residual.

$$y = \beta_o + \sum_{i=1}^{k} \beta_i x_i + \varepsilon \tag{2}$$

$$y = \beta_o + \sum_{i=1}^{k} \beta_i x_i + \sum_{i<j} \sum \beta_{ij} x_i x_j + \varepsilon \tag{3}$$

$$y = \beta_o + \sum_{i=1}^{k} \beta_i x_i + \sum_{i<j} \sum \beta_{ij} x_i x_j + \sum_{i=1}^{k} \beta_{ii} x_i^2 + \varepsilon \tag{4}$$

According to orthogonal test results, the surface roughness prediction model based on feedback engagement *f*, cutting depth *ap*, tool wear *VB* is established as equation (5):

$$R_a = 0.43 + 0.52A + 0.35B + 1.05C + 1.06A^2 - 0.15B^2 + 0.71C^2 \tag{5}$$

Here, $A = \frac{(f - 0.0825)}{0.1175}$, $B = \frac{(a_p - 0.125)}{0.075}$, $C = \frac{(V_B - 0.1675)}{0.1325}$.

According to orthogonal test results, the plastic deformation layer thickness predicate model based on feedback engagement *f*, cutting depth a_p, tool wear *VB* and plastic deformation layer thickness *h* is established as equation (6). After the data is processed, the thickness of model is obtained:

$$h = -0.34 - 0.49A - 0.23B + 1.01C + 0.06A^2 + 0.65B^2 + 0.60C^2 \tag{6}$$

Before modeling, the variables of the model are normalized. The date processing method is as follows:

$$A=\frac{(f-0.1393)}{0.035},\quad B=\frac{(a_p-0.1336)}{0.09},\quad C=\frac{(V_B-0.1812)}{0.1},\quad de=\frac{(d-9.7857)}{5.5}.$$

5. Surface Integrity Modeling based on Multi Objective Optimization Algorithm

Standard particle swarm optimization algorithm cannot be deal with multi-objective problem, so it needs to be changed. This paper mainly changes the algorithm of gbest and pbest. To improve particle swarm optimization algorithm pbest, Pareto decision method is selected. The improved PSO algorithm is adopted for population initialization. And the position of population is generated randomly. The fitness value of particles is calculated according to the objective function. According to decision method of Pareto, the pbest of particle is calculated by judging fitness values. Gbest is solved according to the improved particle swarm optimization algorithm. To determine whether the number of iterations is satisfied, if the requirements are fulfilled, then the calculation is over, otherwise returns to step 2. The target is based on plastic deformation layer thickness and surface roughness has been processed. Multiple objective optimizations are carried out by using the improved particle swarm optimization algorithm. The initial value of the improved particle swarm algorithm is as followed. The population number is 30, the iteration number is 120, c_1 equals 0.279, and c_2 equals 0.54.

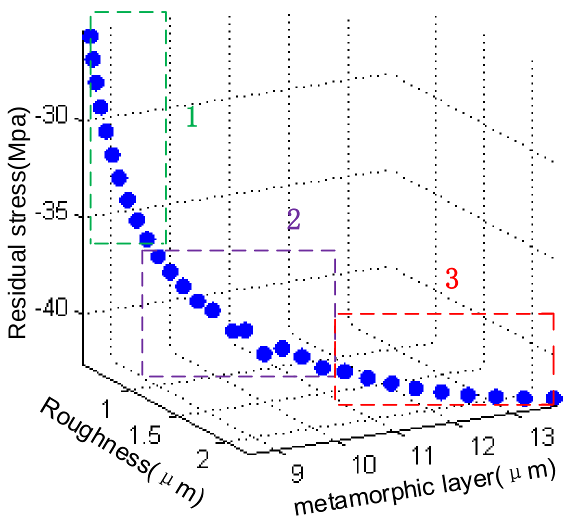

Figure 4. Plastic Deformation Layer Thickness and Surface Roughness of Pareto Front

The final optimization results are shown in Figure 4, which can be seen from the graph, and all of 30 points converge to the Pareto front, and the frontier of Pareto is composed of three regions, so it is respectively. The first area which contains ten points is the smallest area of surface roughness. The third area which contains ten points is the largest area of plastic deformation layer thickness. The twice area which containing ten points for the equilibrium region of which the surface roughness is relatively small, and plastic deformation layer thickness is relatively large area. Therefore, the point of equilibrium is the final result of optimization, the positions of the representative point and the corresponding surface integrity are shown in Table 2.

Table 2. Position and Surface Integrity of Equilibrium Region

Serial number	Feed quantity (r/mm)	Cutting depth (mm)	Tool wear (mm)	Surface roughness (μm)	Plastic deformation layer thickness (μm)
1	0.13	0.14	0.18	1.002	8.788
2	0.13	0.15	0.19	1.109	9.006
3	0.14	0.16	0.2	1.39	9.819
4	0.14	0.17	0.21	1.436	10.07

6. Conclusions

In this paper, the surface integrity of the multi objective optimization is researched for the PCBN tool hard cutting hardened steel Cr12MoV process. The prediction model of surface roughness and surface modification layer was established by using the reaction surface method. The model predicate results show that the increase of cutting depth and feed rate cause increase of surface roughness. With increase of tool wear, plastic deformation layer thickness increases. With the increase of cut depth, plastic deformation layer thickness decreases. The study of the maximum plastic deformation layer thickness and the minimum surface roughness are carried out by improved particle swarm optimization algorithm. The optimization results converge to the Pareto front preferably. The typical surface integrity parameters were obtained. The results of this paper provide a variety of parameters for optimizing the cutting process, and also provide a method for the multi objective optimization of the surface integrity for hard turning process.

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References

[1] Y. Cai xu, L. Xian li, "Journal of Harbin University of Science and Technology", vol. 16, no. 6, **(2011)**.
[2] L.Tang, C. Gao, J. Huang, "The International Journal of Advanced Manufacturing Technology", vol. 77, no. 9, **(2015)** .
[3] T. Thepsonthi, T. Öze, "The International Journal of Advanced Manufacturing Technology", 63, pp. 9-12 **(2012)**
[4] V. S. Sharma , S. Dhiman, R. Sehgal, S. K. Sharma, "Journal of Intelligent Manufacturing", vol. 19, no. 4 **(2008)**.
[5] H. Aouici, "Mohamed Athmane Yallese, Brahim Fnides Journal of Mechanical Science and Technology", vol. 25, no. 11 **(2011)**.
[6] U. Çaydaş, S. Ekici, "Journal of Intelligent Manufacturing", vol.23, no. 3, **(2010)**.
[7] S. Han, "Mechanisms and modeling of white layer formation in orthogonal machining of steels[D]", Georgia: Georgia Institute of Technology, **(2006)**.
[8] J. Kimura and H. Shibasaki, "Editors. Recent Advances in Clinical Neurophysiology", Proceedings of the 10thinternational conference EVOLVE, **(2012)** August 07-09; Mexico City, Mexico.