Optimization Algorithm of Hobbing Cutting Parameters Based on Particle Swarm Optimization SVR

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Abstract: Hobbing cutting technology is of great significance for improving production efficiency and developing cleaner production. However, the choice of optimal hobbing parameters is the key to improving hobbing machining efficiency. To solve this problem, this paper proposes an optimization algorithm of hobbing cutting parameters based on particle swarm optimization support vector regression (SVR). Firstly, based on the objective function of hobbing optimization in the actual machining process, a multi-objective optimization function is set up with the feed rate and cutting speed as variables and the maximum productivity and minimum production cost as the optimization goals. Then, hobbing cutting parameters are optimized by combining particle swarm optimization and support vector regression. The actual machining tests show that the hobbing cutting parameters after optimization are longer than those before optimization. The experimental results verify the effectiveness of the parameter optimization algorithm.

1. Introduction

Gears are a wide variety of basic transmission parts. The machining accuracy of gears directly affects the transmission accuracy. Therefore, gear manufacturing process is the key to ensure the accuracy of gear processing [1-2]. Hobbing, pinching, and milling are common gear processing methods. Among them, gear hobbing produces gears with good precision and high efficiency, and is the main processing method for gear production. With the use of new types of tool materials, the optimization of the hobbing machine structure has improved the accuracy of gear machining. Analyzing the variation of cutting force, cutting temperature and tool wear during the machining process helps to promote the development of hobbing technology to newer directions. At present, the selection of hobbing cutting parameters often needs to be determined through the experience of workers. This does not guarantee efficient, low-cost machining of the work-piece. Therefore, how to choose the optimal hobbing parameters is a very important research direction [3-4].

The cutting parameters are determined by factors such as the material of the tool, the material of the work-piece, the cutting conditions, and the load on the machine tool. The results of the selection of hobbing cutting parameters directly affect the machining quality of the gears, the consumption of machine power, and the gear machining efficiency. Domestic and foreign companies have relatively perfect cutting database. The cutting database greatly promotes the economic benefits of machining. In hobbing cutting, the domestic cutting database is not perfect and it is difficult to set the optimal cutting parameters [5].

For the optimization of hobbing cutting parameters, scholars have proposed many methods. The optimization methods such as particle swarm optimization, ant colony optimization, genetic algorithm and differential evolution algorithm are applied to the optimization of hobbing cutting parameters [6-8]. These studies provide a reliable scientific basis for the selection of hobbing cutting parameters, but their scope of use has certain limitations. In order to make the selection of cutting parameters more convenient, it is necessary to continue to study the optimization of hobbing cutting parameters. This paper presents a method for hobbing cutting parameter optimization based

on support vector regression and particle swarm optimization. This method mainly uses the nonlinear mapping feature of the support vector machine and the intelligent search performance of the particle swarm algorithm.

2. Hobbing cutting parameters optimization model

2.1 Optimize objective function

The objective function of the cutting amount reflects the economic benefits of the cutting process [9]. The optimization objective function generally has the highest productivity objective function, the lowest production cost objective function and the largest profit rate objective function. Since the profit rate involved in the maximum profit objective function is closely related to the hobbing single process time and the production cost of a single gear. Therefore, the highest productivity and lowest production cost objective function is mainly considered in this manuscript.

The hobbing maximum productivity objective function is

$$t_w = \frac{A\pi d_m}{1000z_0} \left[\frac{z}{f \cdot v} + t_c \cdot C_r^{-\frac{1}{m}} \cdot z \cdot f^{\frac{n}{m}-1} \cdot a_p^{\frac{a}{m}} \cdot v^{\frac{1}{m}-1} \right] \tag{1}$$

where,

$$A = \frac{B}{\cos \beta} + L_1 + L_2 \tag{2}$$

where, B is the gear width, β is the helix angle on the index circle, L_1 is the cutting length of the reel, L_2 is the cut-out length, z is the number of gear teeth, n is the number of spindle rotations, f is the amount of feed, and z_0 is the number of hobs.

The minimum production cost function for hobbing is

$$C_{pr} = \frac{A\pi d_m}{1000z_0} \left[\frac{M \cdot z}{f \cdot v} + (Mt_c + C_t) \cdot C_r^{-\frac{1}{m}} \cdot z \cdot f^{\frac{n}{m}-1} \cdot a_p^{\frac{a}{m}} \cdot v^{\frac{1}{m}-1} \right] \tag{3}$$

where, M is the labor cost, t_c is the time of each tool change. The tool change time includes the tool loading and unloading time, tool setting time and sharpening time.

It is known from the two objective functions that the hobbing target function is related not only to the feed rate, cutting speed, and depth of cut, but also to the machine tool, the hob system, and the modulus, number of teeth, and material and machining accuracy of the work-piece. The depth of cut and the number of passes in the cutting parameters depend on the specific machining conditions. Therefore, the feed rate and cutting speed are the main parameters optimized in this paper.

2.2 Restrictions

Optimization of cutting parameters is limited by cutting speed and feed rate. In actual processing, the cutting variables should meet the following constraints.

The cutting speed is

$$v_{min} \le v \le v_{max} \tag{4}$$

That is

$$g_1(x) = v_{min} - v \le 0 \tag{5}$$

$$g_2(x) = v - v_{max} \le 0 \tag{6}$$

The feed rate constraint is

$$f_{min} \le f \le f_{max} \tag{7}$$

That is

$$g_3(x) = f_{min} - f \leq 0 \tag{8}$$

$$g_4(x) = f - f_{max} \leq 0 \tag{9}$$

2.3 Multi-objective optimization function

In order to effectively solve the optimization contradiction between component targets, the linear weighting method is introduced into multi-objective optimization [10]. The multi-objective functions are each given a certain weight. The weighted objective functions are grouped into a comprehensive evaluation function. The multi-objective optimization function of the hobbing cutting parameters can be expressed as

$$F(x) = \sum_{i=1}^{2} w_i w_i' f_i(x) \tag{10}$$

where w_i is the weight coefficient.

3. Particle Swarm Optimization Support Vector Regression

Particle swarm optimization support vector regression mainly uses the nonlinear mapping feature of support vector machine and the intelligent search performance of particle swarm optimization algorithm. Its basic principle is as follows. First, the discrete relationship between target performance and various influencing factors is obtained through experiments. Then, a nonlinear mapping relationship between input and output target performance is established. That is to say, an input-output nonlinear black box function is established. Finally, the black box function is optimized by using particle swarm optimization.

3.1 Support vector regression

Support vector regression is based on Merce's theorem, transforming input space into a high-dimensional feature space through nonlinear transformation. In this high-dimensional feature space, the problem of finding linear regression optimal hyperplanes is transformed into solving convex programming problems. Therefore, the support vector regression can be used to obtain the global optimal solution.

Set the sample set as $\{(x_1, y_1), \cdots, (x_i, y_i)\}$, $x_i \in R^n$ is the input vector, $y_i \in R^n$ is the output vector. When the sample set satisfies the linear relationship, the problem boils down to the following optimization problem

$$\min \frac{1}{2}|w|^2 + C\sum_{i}^{n}(\xi_i + \xi_i^*)$$
$$\text{st} \quad w \cdot x_i + b - y_i \leq \xi_i^* + \varepsilon \tag{11}$$
$$y_i - w \cdot x_i - b \leq \xi_i + \varepsilon$$
$$\xi_i \cdot \xi_i^* \geq 0$$

When the data set cannot achieve linear regression, the original data set is mapped to high-dimensional feature space through nonlinearity. Implement linear regression in high-dimensional feature space. The inner product operation on the high dimensional feature space can be defined as a kernel function

$$K(x_i, y_i) = \varphi(x_i) \tag{12}$$

The constraint expression is

$$\min \frac{1}{2}\sum_{i,j=1}^{n}(\alpha_i^* - \alpha_i)(\alpha_j^* - \alpha_j)\varphi(x_i) + \varepsilon\sum_{i=1}^{n}(\alpha_i^* + \alpha_i) - \sum_{i=1}^{n}y_i(\alpha_i^* + \alpha_i)$$

$$\text{st} \quad \sum_{i}^{n}(\alpha_i - \alpha_i^*) \leq 0 \tag{13}$$

$$0 \leq \alpha_i \leq C$$

$$0 \leq \alpha_i^* \leq C$$

The regression function is

$$f(x) = \sum_{i=1}^{n}(\overline{\alpha}_i^* - \overline{\alpha}_i)\varphi(x_i) + b \tag{14}$$

3.2 Particle swarm optimization

The particle swarm algorithm was proposed by Kennedy and Eberhart in 1995. The algorithm first initializes a group of random particles and then gradually approximates the optimal solution by iteration.[11] In the each iteration, the objective function value of each particle is calculated. The objective function value is compared with two "extreme values". If it is better than the extreme value, save the current solution as an extreme value. The first extremum is the optimal solution found by a single particle itself, called the individual extremum. [12] The other extreme value is the optimal solution found by the entire particle group, called global extremum. After finding the two optimal values, update the particle's velocity and position according to the following three formulas.

$$v_i = wv_i + c_1r(b_i - p_i) + c_2r(g - p_i) \tag{15}$$

$$p_i = p_i + v_i \tag{16}$$

$$w = 0.4 + (0.9 - 0.4)\frac{j_{\max} - j}{j_{\max}} \tag{17}$$

where, v_i is the speed of the particle; w is the weight of inertia, p_i is the position of the current particle, b_i is the individual extremum, g is the global extremum, r is a random number between (0, 1), c_1 and c_2 is The learning factor, j is the current number of iterations, $j_{\max}$ is the maximum number of iterations.

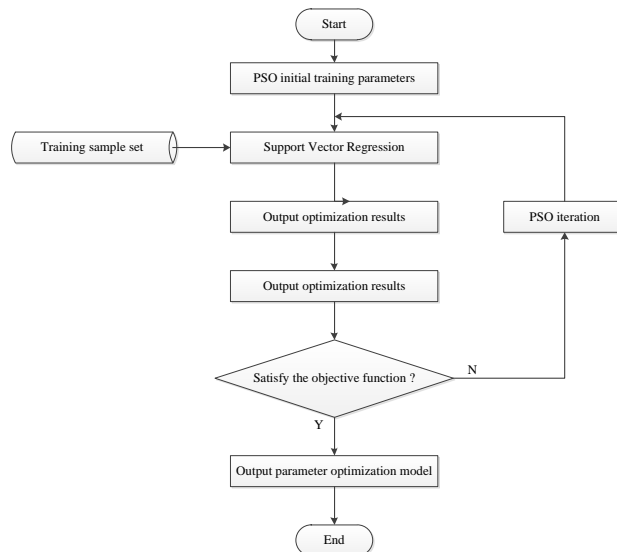## 3.3 Parameter optimization process

Figure 1 Parameter optimization

4. Hobbing cutting parameter optimization study

In the previous section, an optimization model for process parameters in hobbing was established. The model can solve multi-objective optimization functions to obtain the optimal combination of cutting speed and feed parameters. When the parameters are optimized to meet the requirements of actual production and processing, it can be explained that it is a truly effective optimal solution. In order to test whether the parameter optimization based on the particle swarm optimization support vector regression achieves the desired effect, a real machine cutting machining test is needed.

There are two sets of cutting parameters. A set of cutting parameters is the cutting parameters in the production of the company as a reference group. The other group is the optimal combination of cutting speed and feed rate obtained by particle swarm optimization support vector regression and used as a test group. The two sets of parameters are shown in Table 1.

Table 1 Tool life under different parameters

Groups	Cutting speed	Feed rate
Reference group	155m/min	63mm/min
Test group	207m/min	55mm/min

The test is based on the existing processing conditions in the workshop, using the same gear hobbing machine and the same type of hobbing tool. The machining process remains unchanged except for the cutting speed and the feed rate. The hobbing process was performed using the reference group and the test group parameters, respectively. During the machining process, the machined work-piece is extracted every same number. Analyze the life of hobbing cutters under two sets of machining parameters.

When the technical indicators such as processing materials, tool materials, and coating types are the same, the processing cost is negatively related to the tool life. The longer the life of the tool, the lower the processing cost of the gear. The choice of cutting speed and feed rate directly affects the tool life. Therefore, by comparing the tool life under different cutting parameters, it can be judged whether the cost of the two sets of hobbing process is high or low. The experimental results can verify the optimization performance of hobbing cutting parameters based on particle swarm optimization support vector regression. Tool life refers to the number of workpieces that a new tool will process from the time it is started to when it is finally scrapped. Tool life can be translated into the number of work-pieces processed. The test results are shown in Table 2.

Table 2 Tool life under different parameters

	Reference group	Test group
Tool life (number of work-pieces)	783	951

The test results show that the number of work-pieces processed by the cutting parameters of the test group is about 168 higher than that of the reference group, which is increased by about 21%. This reflects the fact that under the cutting parameters of the test group, the degree of influence on the wear and deformation of the tool is reduced, and the adverse effect on the tool life is relatively reduced. Therefore, under the cutting parameters of the test group, the number of work-pieces is slightly increased, and the tool life is also slightly increased.

5. Conclusion

Hobbing has the characteristics of high production efficiency, good versatility, and is a widely used gear processing technology. This paper studies the optimization problem of hobbing cutting parameters, and establishes a multi-objective optimization function with the input and processing speed as variables. Moreover, hobbing cutting parameters were optimized based on particle swarm optimization and support vector regression. The test shows that the optimized cutting parameters

have better processing performance. There is a certain difference between the actual production environment and the theoretical environment. Therefore, whether other cutting parameters meet the requirements also requires further test verification.

Acknowledgements

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