Research on Geometric Error Prediction of High Speed Dry Cutting Gear Hobbing Based on MPGA and BPNN

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Abstract. The geometric error of high-speed dry cutting gear hobbing is affected by many factors, such as process parameters, gear hobbing machine tools and hobs, and it is difficult to predict. This paper uses the vibration of the hob spindle to predict the geometric error, and builds a geometric error prediction model for high-speed dry cutting gear hobbing based on multiple population genetic algorithms and BP neural network. This model comprehensively considers the influence of the hob spindle speed, feed rate and hob spindle vibration on the geometric errors of high-speed dry cutting gear hobbing, which can provide a useful reference for the improvement of gear machining geometric accuracy. Through the experiment, it is concluded that adding the hob spindle vibration during the machining process as the model input can obtain more accurate prediction results of the geometric error of the hobbing machining. Compared with the traditional BP neural network prediction model, this model has better prediction ability.

1. Introduction
Gear is one of the most core transmission components and is widely used in many fields. The demand for gears for high-end manufacturing equipment such as rail transit, precision robots, and new energy vehicles continues to increase, and the requirements for gear processing quality have also increased significantly. High-speed dry cutting gear hobbing is often used as a semi-finishing process for precision gears. It has the advantages of high efficiency and low cost, which affects the efficiency and quality of precision machining such as gear grinding and honing. Studying the relationship between the quality of high-speed dry-cutting gear hobbing and its influencing factors will help improve the quality of high-speed dry-cutting gear hobbing. Improving the quality of high-speed dry cutting gear hobbing can reduce the machining allowance of precision machining processes such as gear grinding and honing, and help improve the overall machining efficiency and quality of precision gears.

There are many main factors that affect the geometric errors of high-speed dry cutting gear hobbing, such as hobs, processing machines, and gear hobbing processes. Experts and scholars at home and abroad have researched many results in these aspects, and made contributions to the development of high-speed dry cutting gear hobbing technology. Regarding the research of gear hobbing tools, the literature [1] proposed a mathematical model of an improved hob with variable gear thickness, which is beneficial to reduce gear surface distortion. The literature [2] conducted a study on the implicit law between the geometric accuracy of gears and the geometric errors of hobs, laying a foundation for the improvement of gear pair accuracy. Regarding the research of gear hobbing machine tools, the literature [3] established a geometric error model of CNC gear hobbing machine and proposed a geometric error compensation strategy. The literature [4] studied the wear performance of the
composite sliding guide of the gear hobbing machine, and provided a useful reference for the design of the oil groove structure and geometric parameters of the guide. Based on an improved Dexel model, the literature [5] proposed a thermal deviation compensation strategy for dry cutting gear hobbing machines. The literature [6] proposed fusion of SVM and multi-objective dragonfly algorithm to optimize the process parameters of low-sample high-speed dry-cutting gear hobbing. The literature [7] proposed an optimization method for gear hobbing process parameters based on BPNN and FPA.

The geometric accuracy of gears is an important index that affects the quality of gears, which can be measured by geometric errors. Gear geometric errors include the total deviation of the gear profile, the total deviation of the helix, the cumulative total deviation of the gear pitch and so on. These errors have a greater impact on the service life, safety and reliability of the equipment. Therefore, in order to obtain a gear that meets the requirements, it is necessary to control the geometric error within the required range.

In the process of high-speed dry cutting gear hobbing, although the strength and rigidity of the machine tool are relatively high, the vibration phenomenon is still unavoidable. The vibration of the hob spindle has a great influence on the geometric accuracy of gear machining. Excessive vibration will reduce the surface quality of the gear and increase the machining geometric error. The study of the influence of the hob spindle vibration on the geometric error of gear machining is helpful to the improvement of the machining performance of high-speed dry cutting gear hobbing machine tools and the quality of gear machining.

There have been related studies on the influence of single factors such as hob, gear hobbing machine tool or gear hobbing process on the geometric error of high-speed dry cutting gear hobbing. However, relatively few studies have comprehensively considered the influence of multiple factors on the geometric errors of gear hobbing. Exploring the influence of multiple factors on the geometric errors of high-speed dry cutting gear hobbing is conducive to the further improvement of gear processing quality. The high-speed dry cutting gear hobbing process has the characteristics of complexity and nonlinearity. The BP neural network with better nonlinear mapping ability is suitable for solving relatively complex problems. However, traditional BP neural networks are greatly affected by parameters such as initial weights and thresholds. Poor model parameter settings can easily lead to defects such as long training time and convergence to local optimal solutions.

Therefore, a geometric error prediction model based on multi-population genetic algorithm and BP neural network for high-speed dry cutting hobbing was established in this paper, which comprehensively considered the influence of technological parameters and hob spindle vibration in the process. Through the comparison of experiments, on the basis of the speed and feed of the hob spindle, the vibration of the hob spindle during the machining process is added as the model input, which can obtain a better prediction result of the geometric error of the high-speed dry cutting gear hobbing. Compared with the traditional BP neural network prediction model, this model has better prediction capabilities.

2. Geometric error prediction model for gear hobbing

2.1. Analysis of geometric error prediction

Because the nonlinear approximation ability is excellent, the BP neural network is very suitable for the establishment of predictive models [8]. The quality of high-speed dry cutting gear hobbing is greatly affected by the process parameters of gear hobbing, and the dynamic and static characteristics of the processing machine tool are also an important factor in the quality of gear hobbing [9]. The vibration of the hob spindle affects the machining accuracy of the gear. Excessive vibration will increase the geometric error of the gear machining. The study of the influence of the hob spindle vibration on the geometric errors of gear machining is helpful to obtain the gear machining accuracy that meets the requirements, and is helpful to the improvement of the machining performance of high-speed dry cutting gear hobbing machine tools and the quality of gear machining. This paper constructs a high-speed dry cutting gear hobbing machining geometric error prediction model, which mainly considers
the influence of the hobbing process parameters and the hob spindle vibration on the gear geometric errors.

The output parameters of the prediction model are the total deviation of the left and right gear profile. The input parameters of the model include machining process parameters and hob spindle vibration influencing parameters. In this paper, the hob spindle speed and feed are selected as the machining process parameters. The vibration acceleration parallel to the hob spindle tangential direction (denoted as X direction), along the hob spindle axis (denoted as Y direction) and along the hob spindle radial direction (denoted as Z direction) are selected as the hob spindle vibration influence parameters. The value of the vibration acceleration of the hob spindle collected during the processing varies between positive and negative. In this paper, the average value of the absolute value of the vibration acceleration during the processing is selected as the model input.

2.2 Geometric error prediction model construction
The production of artificial neural networks is inspired by the operation process of biological neural networks [10]. Combined with statistical methods, a single neuron can have simple analysis capabilities, and a reasonable organization of multiple neurons will be able to handle more complex problems.

BP neural network is a multi-layer feedforward neural network composed of input layer, hidden layer and output layer [11]. Each layer is composed of a certain number of neurons. The same layer is independent of each other, and the layers are fully interconnected [12]. The training of BP neural network mainly carries out the two parts of information dissemination and the correction of connection weights and thresholds. The range of input parameters varies greatly, which will affect the network training time and convergence speed. Input parameters with large values have inconsistent effects on output results compared with input parameters with small values, which will interfere with the accuracy of model training. Therefore, the original data needs to be normalized before training, so that the input amounts are in the same order of magnitude.

The specific training process of BP neural network is shown in Figure 1.

3. MPG and BPNN optimization algorithms
The standard genetic algorithm simulates the evolutionary law of the survival of the fittest through operations such as selection, crossover, and mutation, providing a new way to solve complex optimization problems. The genetic algorithm shows its efficient global optimization ability, but if a
very outstanding individual appears in the population, the individual will rapidly spread in the population. This will cause other individuals in the population to lose their competitiveness and make the algorithm converge to a local solution prematurely. The results of genetic algorithms are also limited by the initial number of individuals in the population, the number of genetic iterations and other parameters. Inappropriate parameters will have a greater impact on the performance of the algorithm.

Multi-group genetic algorithm introduces multiple groups and sets different training parameters to realize the co-evolution of multiple groups on the basis of SGA [13]. The multiple groups do not interfere with each other during training, but after establishing contact through the immigration operator, the search ability of the algorithm is comprehensively improved [14]. MPGA establishes the essence population to store the optimal individuals generated during the evolution of various groups, and the termination basis is the optimal individual maintaining algebra, which is more appropriate than the maximum number of iterations [15].

The initial weight and threshold have a great impact on the predictive ability of BPNN. A poor initial value will cause the network to require a long training time and easily fall into a local minimum. The optimization of the initial weights and thresholds of BPNN through multiple population genetic algorithms will greatly improve the performance of the BP neural network prediction model. The main flow of the algorithm is shown in Figure 2.

The elements of MPGA and BPNN optimization algorithms mainly include the selection of individual coding methods, the setting of objective functions, the setting of immigration operators, and the setting of manual selection operators.

(1) Individual coding and objective function setting

The constructed network structure of the geometric error prediction model for high-speed dry cutting gear hobbing is 5-11-1. When the individual encoding is binary, the length of binary encoding of the individual is 780 when the enactment value and threshold encoding number are both 10. In order to improve the accuracy of model prediction results and optimize the weights and thresholds of BPNN, the error between the real output and the expected output needs to be as small as possible. This article sets the model objective function as the norm of the error matrix.

(2) Immigration operator and manual selection operator setting

The migration operator mainly finds the best individual in a certain population and the worst individual in the target population, and then replaces the worst individual in the target population with the best individual found. The manual selection operator needs to find the optimal individual of each population, record the code of each optimal individual and add it to the elite population.

![Figure 2. MPGA-BP algorithm flow chart](image-url)
4. Instance verification

4.1. Data collection
In order to test the validity of the model built in this paper, a high-speed dry cutting gear hobbing experiment was carried out to collect and verify the required data. In the process of high-speed dry cutting gear hobbing, machining process parameters, machine thermal deformation, hob spindle vibration and hob machining performance will all have an impact on the quality of gear machining. In order to better study the influence of high-speed dry cutting gear hobbing process parameters and hob spindle vibration on the geometric error of gear machining, it is necessary to control the influence of other factors as much as possible during the machining process. The hob used for processing is a new type of hob with a special surface coating treatment. The number of gears that can be processed normally is far more than 50. Therefore, the influence of the hob on the processing can be ignored in the experiment collecting 50 gear processing data. The machine tool is idling before the gear is cut to provide a thermal equilibrium condition to reduce the effect of thermal deformation of the machine tool. The high-speed dry cutting gear hobbing process parameters and the vibration influence parameters of the hob spindle collected in this environment are relatively reasonable as the input of the prediction model.

The collected raw processing data, hob spindle speed and feed are all set within the setting capacity of the processing machine tool, and are relatively evenly distributed. Part of the collected data after sorting is shown in Table 1. The $AX$ is the vibration acceleration parallel to the tangential direction of the hob spindle during processing. The $AV$ is the vibration acceleration along the axis of the hob spindle. The $AZ$ is the vibration acceleration along the radial direction of the hob spindle. The $L_αF$ is the total deviation of the left gear profile. The $F_αR$ is the total deviation of the right gear profile.

| No. | $n$ (rpm) | $f$ (mm/r) | $AX$ (m/s²) | $AV$ (m/s²) | $AZ$ (m/s²) | $L_αF$ (μm) | $F_αR$ (μm) |
|-----|-----------|-------------|-------------|-------------|-------------|-------------|-------------|
| 1   | 1200      | 1.2         | 7.0861      | 9.6269      | 8.6775      | 16.0        | 7.2         |
| 2   | 1200      | 1.6         | 8.1453      | 9.6803      | 8.9473      | 19.2        | 9.0         |
|     |           |             |             |             |             |             |             |
| 49  | 900       | 1.2         | 7.9044      | 8.6662      | 8.8659      | 12.1        | 6.1         |
| 50  | 900       | 1.6         | 9.6273      | 9.1045      | 9.1742      | 21.1        | 7.1         |

4.2. Case comparison verification
For the collected 50 groups of high-speed dry cutting gear hobbing data, 44 groups are selected as the training set, and the remaining 6 groups are the test set to verify the effectiveness of the geometric error prediction model of high-speed dry cutting gear hobbing based on multiple population genetic algorithms and BP neural network in this paper. Set the number of BPNN training terminations to 1000, the convergence accuracy to 0.001, and the learning rate to 0.1. The initial population number of the multi-population genetic algorithm is set to 10, the number of individuals in a single population is set to 40, and the crossover probability of various populations is set in the interval [0.7, 0.9]. The mutation probability of various groups is set in the interval of [0.001,0.05], the generation gap is set to 0.9, and the minimum algebra of the optimal individual is set to 10.

With the improvement of research and development technology, the strength and rigidity of machine tools have gradually improved, but the vibration phenomenon during processing is still unavoidable. The vibration of the hob spindle has a great influence on the geometric errors of gear machining. Studying the influence of the vibration of the hob spindle on the geometric errors of gear machining is helpful to improve the quality of high-speed dry cutting gears.
Construct two high-speed dry cutting gear hobbing geometric error prediction models based on MPGA and BP neural network. One of the models only contains the hob spindle speed and feed, and the other model is based on the hob spindle speed and feed. Based on the quantity, add the X, Y, Z vibration acceleration of the hob spindle as the model input. The prediction results of the total deviation of the left and right gear profile of the two models are respectively shown in Figure 3.

![Prediction result of total deviation](image)

**Figure 3. Prediction result of total deviation**

It can be seen from the figure that the input parameters include the X, Y, and Z three-axis vibration acceleration model of the hob spindle, compared with the input parameters do not include the X, Y, Z three-axis vibration acceleration model, the total gear profile deviation and spiral The predicted result of the total deviation of the line is closer to the actual value.

The model prediction accuracy is compared by the average absolute percentage error. It can better reflect the model prediction performance corresponding to different input parameters. The calculation method is as shown in formula (1). The \( \hat{y}_n \) is the model prediction output value and the \( y_n \) is the expected output value.

\[
MAPE = \frac{1}{N} \sum_{i=1}^{N} \left| \frac{\hat{y}_n - y_n}{y_n} \right| \times 100% \quad (1)
\]

Comparing the average absolute percentage error of the two models, the results are shown in Table 2. If you add the X, Y, and Z vibration acceleration of the hob spindle as the model input on the basis of the hob spindle speed and feed, you will get More accurate gear geometry error prediction results.

| Type       | MAPE value of including vibration | MAPE value of excluding vibration |
|------------|-----------------------------------|----------------------------------|
| \( F_{\text{L}} \) | 7.2624%                           | 10.0723%                         |
| \( F_{\text{R}} \) | 7.8522%                           | 8.8687%                          |

The geometric error prediction model of high-speed dry cutting gear hobbing based on MPGA and BPNN is compared with the traditional BP neural network prediction model. The prediction results of the total deviation of the left and right gear profile are respectively shown in Figure 4.

![Prediction result of total deviation](image)

**Figure 4. Prediction result of total deviation**
It can be seen from the figure that the prediction result based on the MPGA-BP prediction model is closer to the actual value than the prediction result of the traditional BP prediction model.

The model prediction accuracy is compared by the root mean square error, which can better reflect the prediction performance of different prediction models. The calculation method is shown in formula (2). The $\hat{y}_n$ is the model prediction output value and the $y_n$ is the expected output value.

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{n=1}^{N} (\hat{y}_n - y_n)^2}$$  \hspace{1cm} (2)

Comparing the root mean square error of the model, the results are shown in Table 3. The root mean square error of the geometric error prediction model for high-speed dry cutting gear hobbing based on MPGA-BP is relatively small. For the total deviation of the gear profile of the high-speed dry cutting gear hobbing, the prediction of the total deviation of the spiral has higher accuracy.

| Type       | RMSE value of BP model | RMSE value of MPGA and BPNN model |
|------------|------------------------|----------------------------------|
| $F_{\alpha}$ | 1.5951                 | 1.0212                           |
| $F_{\alpha'}$ | 0.7972                | 0.6531                           |

5. Conclusion

This paper comprehensively considers the influence of the high-speed dry-cutting gear hobbing process parameters and the influence of the hob spindle vibration on the geometric accuracy of the gear processing during the machining process, and constructs a high-speed dry-cutting gear hobbing geometric error prediction model based on multiple population genetic algorithms and BP neural networks. The effectiveness of the model is verified through examples. Through test comparison, on the basis of hob spindle speed and feed, adding the vibration acceleration parallel to the tangent direction of the hob spindle, along the axial direction of the hob spindle and along the radial direction of the hob spindle in the machining process as the model input, the better prediction results of high-speed dry cutting hobbing machining geometric error can be obtained. Compared with the traditional BP neural network prediction model, this model has better prediction capabilities. Using the model built in this article to predict and analyze the geometric error of high-speed dry-cutting gear hobbing is helpful to improve the geometric accuracy of high-speed dry-cutting gear hobbing.

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