Data-driven based optimization for high-speed dry cutting gear hobbing processing parameters

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Abstract—The formulation of gear hobbing processing parameters relies on extensive professional knowledge and artificial experience, and inappropriate processing parameters will lead to low machining precision and high manufacturing costs. In order to obtain suitable processing parameters in high speed dry hobbing gear process, Gradient boosting regression (GBR) and Generalized Regression Neural Network (GRNN) are adopted to establish a process parameter optimization model targeting gear machining accuracy and machining energy consumption. And then a method based on Differential Evolution (DE) algorithm, parameter adaptive multi-object differential evolution (AMDE), for hobbing processing parameter optimization is proposed. Machining experiment verification shows that the established gear hobbing accuracy prediction model and energy consumption estimation model have high prediction accuracy, and AMDE has strong optimization capabilities and robustness.

1. INTRODUCTION

Gears are one of the most commonly used mechanical parts in the engineering field. Gear machining accuracy is closely related to service life and failure rate. With the promotion of the concept of green manufacturing and low-carbon production and the motivation to reduce production costs, gear manufacturing companies are also paying more and more attention to the research on reducing machine tool energy consumption. However, according to production experience, a higher spindle speed can improve the precision of gear hobbing to a certain extent, but the high speed parameters will lead to higher processing energy consumption. Therefore, gear manufacturing companies need to find a balance between gear processing energy consumption and machining precision.

At present, many scholars have carried out research on the optimization of process parameters. Cao et al. [1] established a gear hobbing cost model based on empirical knowledge, and used the improved Ant Lion Optimizer to optimize the process parameters. Debkalpa et al. [2] proposed an optimization algorithm that integrates Gravitational Search Algorithm (GSA) and Fireworks Algorithm to optimize
the control parameters of ultrasonic machining. Kharka et al. [3] modeled the process of lubricant-assisted gear hobbing, and used Real-coded Genetic Algorithm to optimize the hob tool speed, axial feed, lubricant flow, air pressure and nozzle angle. Xiao et al. [4] combined data mining technology and fuzzy logic theory, and proposed a two-stage knowledge-driven method to optimize the specific energy consumption and processing time of the washing process.

However, these methods mostly use theoretical analysis and derivation method when modeling the optimization model, and they require extremely professional knowledge and many experience. It makes these methods cannot be directly used for hobbing process parameter optimization under different scenarios and working conditions. The global search performance and robustness of most optimization algorithms are not high enough. Therefore, it is necessary to design a data-driven gear hobbing optimization model to adapt to different types of machine tools. And it also need to improve the performance and robustness of optimization algorithm.

To sum up the analysis above, in order to optimize the process parameters of high-speed dry cutting gear hobbing, an optimization method is proposed. First, a data-driven gear hobbing precision and an energy consumption model are established, the GBR algorithm [5] is used to train the gear processing accuracy prediction model, and then the GRNN algorithm [6] is used to establish the gear hobbing energy consumption estimation model. Finally, a parameter adaptive multi-object differential evolution AMDE is proposed to search for the optimal process parameters. The flowchart of this method is shown in Fig. 1.

**Figure 1. Proposed Gear Machining Processing Parameter Optimization method**

### 2. DATA-DRIVEN BASED GEAR HOBBING OPTIMIZATION MODEL

According to the characteristics of high-speed dry cutting gear hobbing process, the optimization model of high-speed dry cutting gear hobbing based on data drive is designed. The optimization model consists of machining precision prediction model and gear processing energy consumption estimation model.
2.1. GBR for Gear Machining Precision Prediction Model

GBR is essentially an ensemble learning method. Its basic idea is to generate and integrate several weaker learning models to form a stronger learning model [7]. The optimization objective of each weaker learning model is to fit the negative gradient of the loss function of the previous cumulative model, so that the cumulative model loss after adding the weaker learning device decreases to the direction of negative gradient. It is a technique of learning from mistakes. The main difference between GBR's boosting method and Random Forest Regression's (RFR) bagging method is that boosting can only be processed serially because of the strong dependence between the base learners. That is to say, boosting is actually an iterative learning process.

Therefore, GBR is used to train the hobbing accuracy model in this paper. The input of the model is the spindle speed $V_s$, feed speed $V_f$, cutting depth $a_T$, cooling air speed $V_w$, number of hob heads $N_t$, hardness of hob coating $Ch$, and base circle $db$ of workpiece gear. That is to say, the input of the GBR-based precision prediction model is $X_{PP} = [V_s, V_f, a_T, V_w, N_t, Ch, db]$. According to our previous research, the quality inspection indicator $f_{\alpha R}$ has a high correlation with the process parameters, so it is selected as the processing accuracy index, which means the output label is $Y_{PP} = [f_{\alpha R}]$.

2.1.1. Loss function selection

The available loss functions of GBR mainly include least squares (ls), least absolute deviation (lad), quantile loss, and huber loss. The expressions are as follows, where $\hat{y}$ is predictive value.

$$
\text{loss}(ls) = 1/2(\hat{y} - y_{\text{raw}})^2
$$

$$
\text{loss}(lad) = |\hat{y} - y_{\text{raw}}|
$$

$$
\text{loss(quantile)} = \sum_{i:y_i < \gamma} (1-\gamma)|y_{\text{raw}} - \hat{y}_i| + \sum_{i:y_i \geq \gamma} \gamma|y_{\text{raw}} - \hat{y}_i|
$$

$$
\text{loss(huber)} = \begin{cases} 
\frac{1}{2}(y_{\text{raw}} - \hat{y})^2, & \text{if } |y_{\text{raw}} - \hat{y}| \leq \delta \\
\delta|y_{\text{raw}} - \hat{y}| - \frac{1}{2}\delta^2, & \text{otherwise}
\end{cases}
$$

Among them, huber loss is not sensitive to outliers compared with the other loss functions, which can adapt to the gear machining data set containing outliers due to measurement errors to a certain extent, so as to improve the robustness and generalization performance of the prediction algorithm. According to (4), it is based on absolute error, but becomes square error when the error is very small. We can use the hyper-parameter $\delta$ to adjust the threshold of this error. When $\delta$ tends to zero, it degenerates into mean absolute error (MAE), and when $\delta$ tends to infinity, it degenerates to mean square error (MSE). Therefore, Huber loss is chosen as the loss function of GBR in this paper.

2.2. Gear Machining Energy Consumption Estimation Model Based on GRNN

In gear hobbing process, the greater the spindle speed, feed speed and other manufacturing parameters, the greater the peak power of the cutting spindle. The energy consumption of the machine tool is mainly related to the spindle speed $V_s$, feed speed $V_f$, cold air wind speed $V_w$, and cutting amount $a_T$. Therefore, $X_{EC} = [V_s, V_f, V_w, a_T]$ is the input of energy consumption estimation model.

Since GRNN is based on radial basis function network, it has good nonlinear approximation performance [8]. Moreover, the network structure of GRNN is relatively simple, the training speed is fast, thus it is suitable for small sample data. In this paper, GRNN is used to train the energy consumption estimation model to estimate the peak power.

The network structure of GRNN is shown in Fig. 2, mainly include four layers, namely input layer, pattern later, summation layer and output layer. The corresponding input is $X_{EC} = [x_1, x_2, ..., x_n] \rightarrow [V_s, V_f, V_w, a_T]$, and the output is $Y_{EC} = [y_1, y_2, ..., y_k] \rightarrow [\text{PeakPower}]$. Refers [9] for the detail GRNN derivation process reference.
In addition, in order to prevent the gradient explosion issue, this paper modifies the kernel radial basis function as follows:

$$
kernel = \exp\left( -\sqrt{\frac{\sum_{i=1}^{n}(x_{\text{test}}^i - x_{\text{train}}^i)^2}{2\sigma^2}} \right)
$$

(5)

### 3. Multi-objective Optimization Method AMDE

According to the modeling in Section 2, the optimization of gear hobbing process parameters is an NP-hard problem. Generally, the main methods to solve this problem are differential evolution algorithm [10], genetic algorithm [11] and so on. In this paper, an improved parameter adaptive multi-objective differential evolution algorithm AMDE is proposed, the optimization objects are gear machining error and gear cutting peak power. The main idea of AMDE is to design a variety of mutation operators, and adjust the selection probability of different mutation operators adaptively according to the number of iterations. At the same time, a mutation probability parameter $AP$ and a crossover probability parameter $AC$ are designed which can adaptively adjust with iterations. Its purpose is to accelerate the algorithm convergence in the early stage of the iteration, and increase the population diversity in the later stage of the iteration to ensure that the algorithm has a strong ability to jump out of the local optimal solution.

#### 3.1. Coding Method

AMDE uses floating-point coding $\text{Ind}_a = [V_s, V_f, V_w, a_T]$, which means the optimization objects are the spindle speed, feed rate, cooling wind speed, and cutting depth. The population size $P_{\text{size}}$ needs to be preset. When the AMDE algorithm starts to execute, $P_{\text{size}} \text{Ind}_a$ will be randomly generated as the initial population.

#### 3.2. Fitness Function

According to the modeling in the second section, this article has two optimization goals, namely gear machining error and cutting spindle peak power, as shown below.

$$
\text{FitFunc} = \begin{cases}
    f_1: \text{Gear Machining Error, Minimize} \\
    f_2: \text{Machining Peak Power, Minimize}
\end{cases}
$$

(6)

#### 3.3. Mutation and Crossover Operator

Here, two mutation operators, random neighborhood mutation operator and single-element mutation operator, have been designed.

The first is random neighborhood mutation operator $\text{Mut}_1$, as shown in (7). This kind of mutation operator will change all four parameters in $\text{Ind}_a = [V_s, V_f, V_w, a_T]$ according to (7) at the same time when it is executed, and the mutation degree of individual is generally greater. Where $R_{\text{max}}$ and $R_{\text{min}}$ are preset parameters to control mutation scale.
The second is single-element mutation operator Mu2, as shown in Fig. 3. This mutation operator only randomly changes 1 parameter in $Ind_i=[V_s, V_f, V_w, aT]$ during execution, and it generally has a lower mutation degree of individual.

$$Mu_2: \quad Ind_{\text{new}} = Ind_i + R_m [N(Ind_i, \sigma_m)$$

$$- N(Ind_i, \sigma_m)]$$

(7)

Figure 3. Random Single Point Mutation Operator

In addition, AMDE will also perform crossover operations on individuals.

3.4. Adaptive Probability Parameters

For the fixed parameter DE algorithm, its global optimization capability and robustness are negatively correlated. Therefore, we design a series of adaptive parameters in this section, so that the proposed AMDE algorithm has different characteristics at different stages of iteration, and has strong ability of escape from the local optimum and high robustness at the same time. Here, $MaxGen$ is the maximum iteration number, and $\text{iter}$ is the current iteration number.

As for mutation probability, an adaptive mutation probability operator $AP$ is designed as (8). As the number of iterations increases, $AP$ gradually increases and eventually reaches $2pm$. This helps to ensure population diversity at the later stage of the algorithm iteration.

$$AP = pm + pm \times e^{\left(\frac{MaxGen}{\text{iter}} - 1\right)}$$

(8)

In similar way, an adaptive crossover probability operator $AC$ is designed as (9). $AC$ decreases with the number of iterations increases. This adaptive parameter helps the algorithm to achieve convergence in the later stage.

$$AC = pc_{uo} - \frac{\text{iter}}{MaxGen} \times pc_{uo}$$

(9)

3.5. Pareto Dominance

In order to optimize the multi-objective model, Pareto optimization is introduced. At the same time, the concept of crowding degree $Cd_i$ is introduced, as shown in 10. When multiple individuals belong to the same Pareto solution level set, the individuals with large $Cd_i$ are better and rank forward.

$$Cd_i = \begin{cases} +\infty, & \text{if } i \text{ is the boundary} \\ \sum_{j=1}^{m} \frac{f_j(i+1)-f_j(i-1)}{f_j(N)-f_j(1)}, & \text{else} \end{cases}$$

(10)

4. EXPERIMENT AND VALIDATION

4.1. Experimental Setup

In order to verify the method proposed in this paper, a high-speed dry cutting hobbing machine YDS3126CNC is used to machining gears to obtain gear experimental data. The layout of experimental equipment is shown in Fig. 4. Gear hobbing experiment is carried out according to the processing parameters in Table 1, and the $ffaR$ value of each sample is measured as gear precision indicator. At the
same time, the peak power of cutting spindle is read through the CNC system. A total of 230 samples were processed.

**TABLE 1. GEAR HOBBING EXPERIMENT PROCESS PARAMETERS, QUALITY INDEX AND PEAK POWER**

| No. | Process Parameters | ffaR(μm) | Peak Power(W) |
|-----|--------------------|----------|---------------|
| 1   | 63.1669 375 12.5 4.719 10 2 | 2600     | 13.150 1150   |
| 2   | 65.0811 800 90 4.725 20 1 | 3000     | 20.100 4300   |
| 3   | 65.0811 1100 85 4.725 15 2 | 3200     | 17.775 4550   |

**Figure 4. Experimental Equipment Layout**

4.2 Method Validation

4.2.1 Performance Validation of Gear Machining Precision Prediction Model

In order to verify the performance of gear machining accuracy prediction model based on GBR, the regression algorithm comparison test was conducted. Generally, $MSE$, $MAE$ and $R^2$ score ($R^2$) are used to evaluate the accuracy of regression prediction models, shown as (11) to (13).

$$MSE = \frac{1}{N_S} \sum_{n=1}^{N_S} (\hat{y}_n - y_{n, true})^2$$

(11)

$$MAE = \frac{1}{N_S} \sum_{n=1}^{N_S} |\hat{y}_n - y_{n, true}|$$

(12)

$$R^2 = 1 - \frac{\sum_{n=1}^{N_S} (\hat{y}_n - y_{n, true})^2}{\sum_{n=1}^{N_S} (y_{n, true} - \bar{y}_n)^2}$$

(13)

In the test, GBR is compared with Multi-layer Perceptron regression (MLPR), Decision Tree regression (DTR) and RFR. Each algorithm runs 10 times, the prediction error and score are listed in Table 2. Fig. 5 shows the prediction results of one group.

It can be seen from Fig. 5 that the prediction error volume of GBR is smaller than that of the other three algorithms. Table 2 also shows that the performance of GBR is better than other regression algorithms.
TABLE 2. PREDICTIVE PERFORMANCE OF EACH REGRESSION ALGORITHM

|        | MSE↓ | MAE↓ | R2↑ |
|--------|------|------|-----|
| MLPR   | 0.102512 | 0.08399 | 0.5626 |
| DTR    | 0.008023 | 0.05852 | 0.6577 |
| RFR    | 0.003780 | 0.04422 | 0.8387 |
| GBR    | 0.002237 | 0.03708 | 0.9045 |

4.2.2. Performance Validation of Gear Machining Energy Consumption Estimation Model

In order to verify the accuracy of energy consumption estimation model based on GRNN, the prediction performance of GRNN is tested. 50 samples were randomly extracted from the samples training set, and other 10 samples were selected as the test set. The estimation effect is shown in Table 3. The prediction accuracy R2 score is up to 0.9812, which is due to the strong nonlinear fitting ability of GRNN.

TABLE 3. ESTIMATION PERFORMANCE OF GRNN BASED CONSUMPTION ESTIMATION MODEL

| No. | True value | Estimate Value | Error Value |
|-----|------------|----------------|-------------|
| 1   | 1350       | 1318.6         | 31.4        |
| 2   | 2200       | 2270           | 70          |
| 3   | 4750       | 4798.3         | 48.3        |
| 4   | 1300       | 1245.2         | 54.8        |
| 5   | 2800       | 2633.5         | 166.5       |
| 6   | 2650       | 2474.6         | 175.4       |
| 7   | 2300       | 2722.4         | 422.4       |
| 8   | 5100       | 5000           | 100         |
| 9   | 4800       | 4750           | 50          |
| 10  | 2500       | 2771.1         | 271.1       |

Figure 5. Gear machining precision predictive accuracy of (a) Multi-layer Perceptron regression, (b) Decision Tree regression, (c) Random Forest regression and (d) Gradient Boost regression
4.2.3. Performance Validation of Processing Parameter Optimization Method
In order to verify the performance of the proposed AMDE processing parameter optimization algorithm, it was compared with the DE and NSGA-II algorithm. The Pareto Front calculated by each optimization algorithm is shown in Fig. 6. The Pareto Ratio during the iteration process is shown in Fig. 7.

![Figure 6. Pareto Front of AMDE, DE, and NSGA-II](image)

![Figure 7. Pareto Ratio of AMDE, DE, and NSGA-II in Iteration](image)

It can be seen from Fig. 6 that AMDE's Pareto Front basically dominates all DE's and NSGA-II's Pareto Front, which shows that the proposed AMDE method has stronger global search capabilities. It can be inferred from Fig. 7. The DE algorithm converges to the local optimal solution prematurely due to its monotonous variation performance; the NAGA-II has weaker optimization ability and does not converge within the limited maximum iteration. AMDE benefits from the adaptive parameters designed in this paper, which enables it to perform a global search in the early stage of the iteration and a local search in the later stage. Therefore, AMDE has better global optimization capabilities.

5. Conclusion
In this paper, aiming at the problems of gear hobbing process modeling and insufficient searching capabilities of traditional optimization methods, a GBR-based gear hobbing accuracy prediction model and a GRNN-based energy consumption estimation model are designed, and a parameter adaptive processing parameter optimization algorithm AMDE is proposed. The experimental results show that the designed GBR-based gear hobbing precision prediction model and the GRNN-based energy consumption estimation model have considerable prediction ability, and their R2 scores reached 0.9045 and 0.9812, respectively. Furthermore, the optimal solution search ability of the proposed AMDE is higher than the traditional DE and NSGA-II algorithms.
In follow-up research, we will expurgate some unimportant processing parameters involved in precision model training to reduce the computational complexity while ensuring the prediction accuracy.

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