Prediction of processing time and energy consumption and optimization of machining parameters in gear hobbing

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Abstract. This paper studied the characteristics of time and energy consumption of gear hobbing in batch production of small modulus gear. A method of integrating design of experiment, response surface method and multi-objective salp swarm algorithm (DOE/RSM/MMSA) is proposed for the complex optimization of machining parameters (namely hob rotation speed, cutting feed and depth of cut) in gear hobbing process. This paper uses three-level factorial design method to design gear hobbing experiments, and carries out mathematical and statistical analysis on the experimental results. It is found that cutting feed is the most significant machining parameter followed by hob rotation speed and depth of cut to reduce processing time and energy consumption. The prediction model of processing time and energy consumption in gear hobbing process is obtained through response surface methodology. The relative error rates of the predicted value and the actual value of the processing time and energy consumption are 0.11% and 0.09% respectively, indicating the validity of the model. Multi-objective salp swarm algorithm is used to optimize the machining parameters to minimizing processing time and energy consumption. Finally, through the comparison with the existing research results, it is concluded that the optimized machining parameters have better processing effect to achieve minimized processing time and energy consumption, which shows the effectiveness and rationality of the method proposed, and provides references for the decision-making of machining parameters in workshop.

Nomenclature

$D_{\text{max}}$ Maximum workpiece diameter (mm)
$m_{\text{max}}$ Maximum workpiece module (mm)
$n_{\text{max}}$ Maximum hob spindle speed (r/min)
$m_{0}$ Workpiece normal module (mm)
$Z_1$ Number of workpiece teeth
$\alpha$ Workpiece normal pressure angle (rad)
$\beta$ Workpiece helix angle (rad)
$d_{a1}$ Workpiece outside diameter (mm)
b Face width (mm)
$d_{a0}$ Tip diameter of hob (mm)
1. Introduction

With the concept of low carbon manufacturing and green manufacturing, more and more scholars have invested in the research of energy efficiency and carbon emissions in mechanical processing. The related research shows that the environmental performance can be improved by optimizing the machining parameters and the efficiency and green of the machine tool can be improved. Many scholars are devoted to the study of optimization of machining parameters in different manufacturing methods.

D’Addona and Teti proposed an optimization paradigm based on genetic algorithms (GA) to seek optimal cutting parameters in turning processes that lead to reduction in production cost and time as well as enhancement in production quality [1]. Sreeram et al. reported GA-based optimization of cutting parameters method in micro-end-milling operations that ensure maximum tool life and minimum possible production cost without violating any of the imposed constraints [2]. Cao presented a hybrid improved back propagation neural network/differential evolution (IBPNN/DE) approach to do a continuous optimization decision making of process parameters in high-speed gear hobbing [3]. Cao first proposed a support vector machine/ant lion optimizer/gear hobbing (SVM/ALO/GH) integrated approach to do the multi-objective optimization of machining parameters for solving small sample problem of batch production [4].

The energy consumption in processing has been paid more attention and became a hot spot of research. Mori et al. suggested an energy evaluation function of machine tools and got the conclusion that modifying cutting conditions reduces energy consumption [5]. Garg and Lam proposed a new ensemble-based MGGP (EN-MGGP) approach to optimize analytically for attaining the optimum input parameter settings that optimize the product quality and power consumption simultaneously [6]. Wang et al. provided the multi-objective optimization method of machining parameters considering energy consumption but was still limited in cutting process category and optimization algorithm [7]. Velchev et al. proposed an improved parametric model to research the relationship between the specific energy consumption and parameters during CNC turning [8]. Campatelli et al. applied RSM to obtain the regression model so as to explore the effect of cutting speed, feed rate, radial and axial depth of cut on energy consumption during a milling process [9]. Kuram et al. dealt with the assessment of vegetable-based cutting fluids for end-milling. For this purpose, the effects of cutting fluid types were investigated as a function of three milling factors (cutting speed, depth of cut, and feed rate) on process responses (specific energy, tool life, and surface roughness). D-optimal method was conducted to develop mathematical models for process responses [10].

Based on the above, it is found that the current research focus for optimization of machining parameters mainly on the process of turning [1, 8], milling [2, 7, 9, 10] and grinding machining [11]. The machining process of hobbing is relatively complex. At present, there are few researches on the optimization of the machining parameters of hobbing. Only Cao [3, 4] has carried out the specific study. Cao uses historical processing cases as research support and research data source, and establishes a
parameter decision model by algorithm. However, the processing history case belongs to the processing result of the empirical parameters, and the reasonable experimental design is not carried out. The case mainly focuses on several commonly used or one processing parameters. There are few or no cases that exceed those limits, which limit the universality, validity and rationality of the optimized model.

Gear as an important transmission part, its processing process is more complex than the general parts. Its processing methods include hobbing, inserting and grinding, etc. It is very important to optimize the machining parameters to save energy and time. This paper studied the characteristics of gear hobbing in batch production of gears. At present, no relevant scholars have used the method of experimental research to study the relationship between the energy consumption and the processing time of gear hobbing and the machining parameters. The response surface method is used to design and analyze the hobbing process experiment for the first time in order to fill this research hole in this paper. The effects of machining parameters (hob rotational speed, cutting feed and depth of cut) on the processing effect (processing time and energy consumption) are systematically studied. The regression mathematical model and multi-objective optimization model of processing time and energy consumption are given, and the efficient multi-objective salp swarm algorithm is used to solve the problem.

2. Problem description
In this paper, the characteristics of time and energy consumption of gear hobbing in the batch production of small modulus gear are studied, and we focus on gear hobbing of gears with a modulus of less than 3mm, which machined by one-pass. The machining characteristics of hobbing are systematically studied by experimental investigations. The experimental data in this paper are obtained through reasonable experimental design and implementation. In order to embody the rationality and effectiveness of the research, 27 sets of experiments were designed by 3-level factorial design.

In the multi-objective optimization problem of hobbing process, there are usually four evaluation indexes: energy consumption, processing time, machining quality of hobbing and hobbing cost. The key point of this paper is to study the nonlinear relationship between processing time and energy consumption and hobbing parameters. Therefore, in the multi-objective optimization model, the processing time and energy consumption as the objective function, the machining quality of hobbing and the hobbing cost as constraints. Taking the minimum processing time and energy consumption as the optimization objective, gear hobbing parameters (hob rotation speed, cutting feed and depth of cut) are taken as decision variables.

3. Research methodology
The energy consumption optimization of hobbing parameters is a NP problem with nonlinear, multivariable, multi-objective, constrained and coupled properties. In this research, a multi-objective optimization method combined with DOE/RSM/MSSA is proposed. 3-level factorial design, response surface methodology (RSM) [12-13] and multi-objective salp swarm algorithm (MSSA) [14] are applied to design experiments and analyze experimental data, and explore the nonlinear relationship between energy consumption and processing time and hobbing machining parameters in hobbing process. At the first stage, 3-level factorial design is used to collect experimental data and preliminarily study the relationship between objectives and parameters. The multi-objective optimization is meaningful only when looking for trade-off between conflicting objectives. In this case, RSM models are built to approximate target functions, so a multi-objective model is easy to acquire. In this research, an efficient and accurate method for analyzing the energy consumption characteristics and processing time of hobbing process is presented. Figure 1 illustrates the framework of the integrated method in this research.
4. Experimental design and conduct

The experiment involves (i) a CNC high speed gear hobbing machine, (ii) some gear blanks, (iii) a computer, (iv) energy consumption monitoring system (LDMS) [15], (v) design-export software. The optimization process program is transformed to NC codes by technicians.

Measuring instruments and systems is represented in Figure 2. The processing time is obtained by the cutting time view function on user interface of SINUMERIK 840Dsl CNC system. The energy consumption is achieved using energy consumption calculation function of LDMS.

The experiment was carried out in a gear manufacturing plant of some manufacture enterprise in Chongqing, China. The machine tool is YS3120CNC6-S. The one is a CNC high speed gear hobbing machine with six axes and four linkages. The main specifications of the machine tools are shown in Table 1, which gives the parameter requirements for the gears to be processed in the experiment. The type of workpiece was a cylindrical gear. The material for the workpiece was 20CrMo. TiAlN coated S390-based hobs were applied. Hobbing parameters and their levels are given in Table 2. It is assumed that the conditions of each group of experiments are the same except the given variables. The experimental data designed with 3-Level Factorial in Design-Expert.8.05b is shown in the table 3. The results of each experiment were the average of the three measurements.

| Symbol | Level 1 | Level 2 | Level 3 |
|--------|---------|---------|---------|
| \( n \) | 369.00  | 410.00  | 451.00  |
| \( f \) | 1.35    | 1.50    | 1.65    |
| \( d \) | 4.00    | 5.50    | 7.00    |

![Figure 1. Research methodology used in the study](image-url)
5. Experimental design and conduct

5.1. Factor effect analysis
The main and interactive effects of processing time and energy consumption at different levels are shown in Figure 3 and 4, respectively. The main influence factors and the optimal level can be determined from the main effect diagram. The effect of each factor on the responses can be seen from the interaction effect diagram.
As shown in Figure 3, we can see that the effect of hobbing parameters on processing time and energy consumption is similar. When hob rotation speed $n = 451 \text{ r/min}$, cutting feed $f = 1.8 \text{ mm/r}$ and depth of cut $d = 4.00 \text{ mm}$, processing time and energy consumption are the least. As shown in Figure 4, it is found that cutting feed is the most significant machining parameter followed by hob rotation speed and depth of cut to reduce processing time and energy consumption. It can be found that the larger hob rotation speed and cutting feed, the smaller depth of cut, the less processing time and energy consumption.

![Main Effects Plot for Tp](image-url)

![Main Effects Plot for Pc](image-url)

**Figure 3.** Main Effects Plot for $Tp$ and $Pc$
5.2. *RSM model establishment*

In order to facilitate the analysis, the actual values of the gear hobbing parameters are normalized, as shown in Table 4. Hob rotation speed $n$, cutting feed $f$ and depth of cut $d$ correspond to $A$, $B$ and $C$, respectively. The values in the experiment were -1, 0, or 1.
Table 4. The normalized values of hobbing parameters

| Factor | Name | Minimum | Maximum | Coded Values |
|--------|------|---------|---------|--------------|
| A      | $n$  | 369.00  | 451.00  | $A = \frac{n - 410.00}{41.00}$ |
| B      | $f$  | 1.40    | 1.80    | $B = \frac{f - 1.60}{0.20}$    |
| C      | $d$  | 4.00    | 7.00    | $C = \frac{d - 5.50}{1.50}$    |

Regression statistics after the normalization is shown in Table 5. The "Pred R-Squared" of 0.9996 is in reasonable agreement with the "Adj R-Squared" of 0.9998 in $Tpp$. And the "Pred R-Squared" of 0.9995 is in reasonable agreement with the "Adj R-Squared" of 0.9997 in $Pcp$. The "Adeq Precision" measures the signal to noise ratio. A ratio greater than 4 is desirable. Our ratio of 366.480 in $Tpp$ and ratio of 366.480 in $Pcp$ indicate an adequate signal. This model can be used to navigate the design space.

Table 5. Regression statistics

| Type     | $Tpp$       | $Pcp$       |
|----------|-------------|-------------|
| Std. Dev.| 0.35        | 0.0005378   |
| Mean     | 194.78      | 0.38        |
| C.V. %   | 0.18        | 0.14        |
| PRESS    | 5.10        | 0.00001174  |
| R-Squared| 0.9998      | 0.9998      |
| Adj R-Squared | 0.9998 | 0.9997 |
| Pred R-Squared | 0.9996 | 0.9995 |
| Adeq Precision | 366.480 | 324.426 |

The analysis of variance is shown in Table 6. The Model F-value of 21201.86 in $Tpp$ and the Model F-value of 11858.73 in $Pcp$ imply the models are significant. There is only a 0.01% chance that a "Model F-Value" this large could occur due to noise.

Table 6. Analysis of variance table

| Type | Source | Sum of Squares | df | Mean Square | F Value | p-value | Prob > F |
|------|--------|----------------|----|-------------|---------|---------|----------|
| $Tpp$| Model  | 13604.53       | 9  | 2267.421    | 21201.86| < 0.0001| significant |
|      | Residual | 2.138889    | 17 | 0.106944   |         |         |          |
|      | Cor Total| 13606.67     | 26 |             |         |         |          |
| $Pcp$| Model  | 0.025919      | 9  | 0.00324     | 11858.73| < 0.0001| significant |
|      | Residual | 0.00000492   | 17 | 0.000000273|         |         |          |
|      | Cor Total| 0.025924     | 26 |             |         |         |          |

Table 7. Regression coefficient and other statistical values of $Tpp$

| Factor | Coefficient Estimate | df | Standard Error | 95% CI Low | 95% CI High |
|--------|---------------------|----|---------------|------------|-------------|
| Intercept | 191.89              | 1  | 0.18          | 191.51     | 192.27      |
| $A - n$      | -17.11              | 1  | 0.084         | -17.29     | -16.93      |
| $B - f$      | -21.33              | 1  | 0.084         | -21.51     | -21.16      |
| $C - d$      | 1.11                | 1  | 0.084         | 0.93       | 1.29        |
| $AB$         | 2.25                | 1  | 0.10          | 2.03       | 2.47        |
| $AC$         | 0.00                | 1  | 0.10          | -0.22      | 0.22        |
| $BC$         | 0.00                | 1  | 0.10          | -0.22      | 0.22        |
| $A^2$        | 1.67                | 1  | 0.14          | 1.36       | 1.97        |
| $B^2$        | 2.67                | 1  | 0.14          | 2.36       | 2.97        |
| $C^2$        | 0.00                | 1  | 0.14          | -0.31      | 0.31        |
Table 8. Regression coefficient and other statistical values of $P_{cp}$

| Factor | Coefficient Estimate | df | Standard Error | 95% CI Low | 95% CI High |
|--------|----------------------|----|----------------|------------|-------------|
| Intercept | 0.37 | 1 | 0.0002739 | 0.37 | 0.37 |
| $A - n$ | -0.018 | 1 | 0.0001268 | -0.019 | -0.018 |
| $B - f$ | -0.033 | 1 | 0.0001268 | -0.033 | -0.033 |
| $C - d$ | 0.0171 | 1 | 0.0001268 | 0.00145 | 0.001985 |
| $AB$ | 0.002804 | 1 | 0.0001553 | 0.002477 | 0.003132 |
| $AC$ | 0.0003708 | 1 | 0.0001553 | -0.0002905 | 0.0003647 |
| $BC$ | 0.000 | 1 | 0.0001553 | -0.0003276 | 0.0003276 |
| $A^2$ | 0.002224 | 1 | 0.0001553 | 0.00176 | 0.002687 |
| $B^2$ | 0.004112 | 1 | 0.0001553 | 0.003649 | 0.004576 |
| $C^2$ | -0.00003708 | 1 | 0.0001553 | -0.0004668 | 0.0004598 |

According to the above analysis, the regression coefficient and other values can be obtained as shown in Table 7 and Table 8. A regression model for processing time and energy consumption is obtained as follows:

$$T_{pp} = 191.89 - 17.11A - 21.33B + 1.11C + 2.25AB + 1.67A^2 + 2.67B^2$$  \hspace{1cm} (1)

$$P_{cp} = +0.37 - 0.018A - 0.033B + 0.001717C + 0.002804AB + 0.0003708AC + 0.002224A^2 + 0.004112B^2 - 0.00003708C^2$$  \hspace{1cm} (2)

According to the prediction model, the prediction values of 27 sets of experimental data are calculated as shown in Table 3. The relative error rates of processing time and energy consumption are 0.11% and 0.09%, respectively, indicating the effectiveness of the model.

It can be seen from Figure 5 that the effect of hobbing parameters on the processing time and energy consumption is similar, which conforms to the conjecture 1 proposed by Cao [4], which shows the effectiveness of the model and experimental design. During the hobbing process, the larger hob rotation speed and cutting feed are, the smaller depth of cut is, the less processing time and energy consumption are. And the cutting feed has the greatest influence on the objective function value, followed by hob rotation speed and depth of cut, which is consistent with the result of factor effect analysis.

Figure 5. Contour plots of $T_{pp}$ and $P_{cp}$
6. Multi-objective optimization model

In order to use the multi-objective salp swarm algorithm to get the optimal hobbing parameters under the given requirements, a multi-objective optimization model is established to optimize the process parameters.

6.1. Variables and objective function

The prediction models of the processing time and energy consumption obtained by the response surface method are used as the objective function. Taking into account the hobbing parameters on the processing time and energy consumption has an important impact, hob rotation speed, cutting feed and depth of cut are used as decision variables.

6.2. Constraints

6.2.1. Hobbing parameters

\[ lb_i \leq x_i \leq ub_i, i = 1, 2, 3 \]  

where \( x_i \) is the gear hobbing parameter. The optimized hob rotation speed, cutting feed and depth of cut must be within the range of the given maximum and minimum.

6.2.2. Hobbing cost. In the process of hobbing, the cost of hobbing includes the fixed cost and the variable cost. The fixed cost includes material cost, personnel cost, auxiliary cost (cooling system, lighting system, electrical control system, etc.), and variable cost includes tool cost and energy cost. Considering that the fixed cost is the same in the process of hobbing, the variable cost is considered only when the constraint conditions are given, and the calculation formula is as follows:

\[ \text{Cost} = C_p + C_{pcp} \]

The constraint conditions of the hobbing cost can be expressed as follows:

\[ C_p \leq C_A \]

6.2.3. Hobbing quality. Axial feed and hob diameter is the decisive factor in the depth of the tool feed. The quality of gear hobbing is mainly considered by the corrugation height of the tooth surface produced by rolling cutting, and can be calculated by the Eq. (6) given in document [16].

\[ Q = (f / \cos \beta) \sin \alpha / (4d_{a0}) \]

When evaluating the quality of hobbing, the surface roughness of the workpiece is required less than the required precision grade. Namely

\[ Q \leq QR \]

6.3. Optimization model

In summary, the multi-objective optimization model in the hobbing process is as follows:
\[
\min F(n, f, d) = (\min Tpp, \min Pcp) \\
\begin{cases}
lb_i \leq x_i \leq ub_i, i = 1, 2, 3 \\
s.t. \quad Q \leq QR \\
C_p \leq C_A 
\end{cases}
\] (8)

7. Analysis and discussion of the results

7.1. Result analysis

The multi-objective optimization settings and the constants are shown in Table 9.

| Symbol | L  | N  | N_0 | N_v | N_{th} | T_h | C_H | C_v | C_A | QR |
|--------|----|----|-----|-----|--------|-----|-----|-----|-----|-----|
| Value  | 100| 200| 100 | 3   | 2      | 2600| 2800| 0.76| 150 | 3.2 |

**Figure 6.** Value of \( c_i \) in each iteration

**Figure 7.** Salps swarm in each iteration
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The fitness of salps swarm

The multi-objective optimization model in this study is solved by MATLAB R2009a. By modifying the source code of multi-objective salp swarm algorithm provided by Mirjalili [14], we get the change curve of coefficient $c_1$ as shown in Figure 6. After 60 iterations, the value of $c_1$ tends to be stable. After 100 iterations, $c_1 = 2.251 \times 10^{-7}$ indicates that 100 iterations are enough. Salps in each iteration is shown in Figure 7. After completing the 100th iteration, the position of the leader is $A = 1.00$, $B = -0.25$ and $C = -1.00$, that is the solution of the multi-objective optimization model. The objective function values of leaders and followers are shown in Figure 8. The leader’s objective function values are $T_{pp} = 180.28$ and $P_{cp} = 0.363274$ after 100 iterations. So the corresponding hobbing parameters hob rotation speed $n = 451.00$, cutting feed $f = 1.55$ and depth of cut $d = 4.00$.

7.2. Comparative analysis

In order to illustrate the effectiveness and rationality of the optimization results, the optimized parameters are compared with the empirical processing parameters, IBPNN/DE [3] and SVM/ALO/GH [4] optimized results. The actual processing effect is shown in table 10. Compared with the processing effect of experiential processing parameters, the optimized hobbing parameters obtained by this study for gear hobbing can shorten the processing time of 5.76% and save 2.50% of the energy. Compared with IBPNN/DE, the optimized hobbing parameters obtained by this study can shorten 6.25% processing time and save 2.80% energy. And the optimized hobbing processing parameters can shorten processing time by 5.26% and save 1.95% energy in comparison with SVM/ALO/GH.

In summary, we can see that under the premise of ensuring the quality to meet the actual requirements, the research method of this paper is better for parameters optimization of gear hobbing process in small module batch production, which can shorten processing time and reduce energy consumption.

| Type                | $n$  | $f$  | $d$  | $T_{pp}$ | $P_{cp}$ |
|---------------------|------|------|------|----------|---------|
| MSSA                | 451.00 | 1.55 | 4.00 | 180      | 0.363274 |
| Empirical hobbing   | 410.00 | 1.60 | 4.60 | 191      | 0.372583 |
| IBPNN/DE            | 408.00 | 1.60 | 4.59 | 192      | 0.373754 |
| SVM/ALO/GH          | 407.00 | 1.62 | 4.005| 190      | 0.370480 |

8. Conclusion

In this paper, the processing time and energy consumption of hobbing process are studied by the combination of response surface method and multi-objective optimization for the first time. The optimal hobbing parameters are obtained with the goal of minimizing processing time and energy consumption. The experimental results show that the cutting feed has the greatest influence on the processing time and energy consumption, followed by the hob rotation speed and depth of cut. Multi-objective optimization results show that the optimal parameters obtained are more reasonable and have better optimized results than the empirical parameters, IBPNN/DE and SVM/ALO/GH. The research method in this paper is of
great guiding significance for the optimization decision-making of gear hobbing parameters in small module batch production.

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