Study on Basic Experiment and Optimization Prediction Model of Orthogonal Electrolytic Machining of Film Cooling Hole in High Temperature Nickel-Based Alloy Blades

Yulan Hu¹, Weiguang Hao¹, Guoqiang Liu², Yajie Liu², Zilin Liu¹

¹School of Information Science and Engineering, Shenyang Ligong University, Shenyang, China
²School of Mechanical Engineering, Shenyang Ligong University, Shenyang, China

Abstract. The orthogonal test was designed based on high temperature nickel-based alloy Inconel718. The variance analysis was carried out on the test results. The significant factor was determined by the significance test. The model structure was trained by the electrolytic processing test data, and finally the prediction model of the momentum-adaptive learning BP Neural Network is established. The model is used to predict the pore size of stainless steel micropores processed under different processing parameters. The results show that the model has a prediction error of less than 5% and has a strong predictive power.

1. EXPERIMENTAL EQUIPMENT AND MATERIALS

Based on the electrolytic processing method and mechanism, the experimental system for electrolytic processing was constructed as shown in Fig. 1. The experimental system includes an electrolysis motion control portion, an electrolyte constant temperature control portion, and an electrolyte circulation control portion. With servo drive, the feed is stable. The electrolysis power supply uses a high frequency pulse power supply.

The material was made of Inconel 718, a high-temperature nickel-based alloy commonly used for turbine blades, and 50 specimens of 10 mm × 20 mm were cut by a fiber laser cutter. Before processing, the test piece is cleaned and dried by an ultrasonic cleaner.

Figure 1. Electrolytic processing experimental system
2. MAIN FACTORS AFFECTING ELECTROCHEMICAL MACHINING

Electrochemical machining \[6\] is a method based on the principle of electrochemical dissolution of metal anode to machine and shape a workpiece with a shaped cathode tool. Electrical parameters, electrolyte parameters, workpiece characteristics, cathode and other parameters (as shown in Figure 1) are the main factors affecting the processing quality.

The prediction model is studied with the easily measured and easily controlled machining parameters such as current value I, electrolytic voltage U, pulse power frequency F, pulse power duty ratio C, initial machining gap D and electrode feed speed V, etc.

3. ORTHOGONAL EXPERIMENTAL DESIGN AND RESULTS ANALYSIS

Based on orthogonal experiments, this paper finds how to quickly find significant factors from many influencing factors, and analyzes the influence of single factors on the response of each processing parameter. The experiment used 6 factors and 5 levels of experiments, a total of 50 groups of experiments. Three wells were processed in each set of experiments and the mean values were taken.

Process parameter level table 1 is as shown:

| factor                        | Level |
|-------------------------------|-------|
|                               | 1     | 2     | 3     | 4     | 5     |
| A. electrolysis voltage (0-24V)| 4     | 7     | 10    | 13    | 16    |
| B. Current value (0-5A)       | 3     | 3.5   | 4     | 4.5   | 5     |
| C. Pulse power frequency (1-10kHz) | 1     | 3     | 5     | 7     | 9     |
| D. Pulse power supply duty cycle (%) | 30    | 40    | 50    | 60    | 70    |
| E. Initial machining gap (μm) | 40    | 45    | 50    | 55    | 60    |
| F. Electrode feed rate (μm)   | 6     | 8     | 10    | 12    | 14    |

Regression variance analysis of inlet roundness. The F-value of the inlet roundness model is 2.44, the corresponding p-value is 0.0404<0.05, and the model is established. It is indicated that the regression equation of the inlet roundness is generally significant, the power supply pulse frequency plays a general role, and the remaining items have less influence on the inlet roundness.

Analysis of the regression variance of the positive side clearance. The F-value of the positive-side gap model is 16.59, and the corresponding P-value is 0.0001, and the model is established. It is indicated that the regression equation of positive side clearance is the most significant, and the power supply voltage and power supply duty ratio play a major role. Power supply pulse frequency is generally significant, the positive side clearance plays a general role. The remaining items have less effect on positive side clearance.

Analysis of the regression variance of the cone degree. The F-value of the positive-side gap model is 9.99, and the corresponding P-value is 0.0001, and the model is established. It is indicated that the regression equation of taper has the most significant effect on the power supply voltage and the duty
ratio of power supply. The pulse frequency of the power supply is generally significant, and it has a
general effect on taper.

4. BP NEURAL NETWORK MODEL DESIGN

4.1 BP network structure design
A BP neural network with a single hidden layer is used to establish a predictive model of the
relationship between processing parameters and the size of the processed micropore. The number of
input layer nodes of the BP network is \( m = 6 \), corresponding to the six processing parameters
mentioned above; the number of nodes of the output layer is \( n = 3 \), corresponding to the upper surface
diameter \( D_1 \) (mm) of the micropore and the surface aperture \( D_2 \) of the micropore (Mm) and
electrolytic processing time \( t(s) \); \( \omega_{ij} \) is the weight of the jth input layer node to the i-th hidden layer
node, and \( \omega_{ki} \) is the weight of the i-th hidden layer node to the kth output layer node , as shown in
Figure 2.

![Typical three-layer BP neural network structure](image)

Figure 2. Typical three-layer BP neural network structure

The number of nodes in the middle hidden layer of the BP network has an important influence on
the learning and calculation of the network. The number of hidden layer nodes is too small, the
network is too simple to meet the accuracy requirements; the number of hidden layer nodes is too
large, the training time is too long, and it is easy to over-fitting so that the generalization ability is poor.
Determine the number of hidden layer nodes based on the following empirical formula:

\[
h = \sqrt{m+n} + b
\]

In the formula, \( h \) is the number of hidden layer nodes, and \( b \) is an arbitrary number from 1 to 10.

4.2 Design Test
The electrolytic part of the micro-machining system is used for electrolytic machining test. The system
mainly consists of gas-assisted laser machining module, high-frequency microsecond pulse
electrolytic power supply, thermostatic electrolyte system, sidewall insulated tubular electrode and
low-concentration acidic passivating electrolyte.

Considering the cost during the test, a bare electrode with a diameter of 0.6 mm, a NaNO\(_3\) solution
with a concentration of 8 %, an electrolyte of 21 ℃, a 1Cr18Ni9 Ti stainless steel sheet with a
thickness of 0.59 mm for the anode workpiece, etc. were used. For the six input layer parameters that
need to be tested, the orthogonal test method is used in the range of effective parameters, which can
greatly reduce the number of tests and make the tests more representative and persuasive. The
parameter design is shown in Table 2.

| NO | U/V | I/A | f/kHz | c/% | d/μm | v/μm |
|----|-----|-----|-------|-----|------|------|
| 1  | 8   | 3   | 1     | 30  | 40   | 10   |
| 2  | 9   | 3.5 | 3     | 40  | 45   | 11   |
| 3  | 10  | 4   | 5     | 50  | 50   | 12   |
4.3 Model training and prediction results analysis

The parameters in Table 1 were designed by orthogonal test method. 50 sets of test data were used to train the improved BP neural network, and the remaining 10 sets of data were used to test the trained BP neural network prediction model. During the training process, it is found that when the number of nodes in the hidden layer is 10, the prediction effect is the best, and the value of each parameter in the improved BP neural network is determined. Among them, the adaptive learning rate initial value $\eta_0 = 0.035$ and $0.015 \leq \eta_1 \leq 0.2$, the momentum factor initial value $mc_0 = 0.65$ and $0.65 \leq mc \leq 0.9$, $\alpha = 0.001$. The target error $E_0 = 4$, when the target error is too small, there will be over-fitting; when the target error is too large, the higher training fit will not be achieved, both of which will greatly reduce the prediction accuracy. A comparison of the predicted and experimental values of the processing time is shown in Figure 3.

At this point, the value of the prediction accuracy is completed. The above process is repeated ten times, and the grouping conditions are different each time, the calculated inlet diameter simulation error is 5.04%, the exit diameter simulation error is 4.15%, and the electrolytic machining time prediction error is 3.29%. The prediction error is within ±15%, compared with the average prediction error of 5.97% obtained by Zheng Xu et al. [8] in optimizing the process parameters in this field, and Wang Lei et al. [9] has an obvious prediction error of 12% in this field. Improve the effect. The prediction results are basically consistent with the actual processing.

![Figure 3. Processing time prediction comparison results, and the validity of the momentum-adaptive learning BP neural network electrolytic machining prediction model is verified.](image)

5. Conclusion

The orthogonal test of the blade film cooling hole was carried out by the experimental processing system built by the independent experiment. The results show that the power pulse frequency has a general effect on the inlet roundness. The power supply voltage and the power supply duty cycle have a major influence on the positive side clearance. The voltage and power supply duty cycle have a major influence on the taper, and the power pulse frequency is generally significant, which has a general effect on the taper. A model for predicting the parameters of electrolysis machining by momentum-adaptive learning BP neural network is proposed. The main processing parameters are selected to determine the model structure of the BP neural network. The orthogonal test was designed by using the existing test system device, and the momentum-adaptive learning BP neural network was trained and tested with the test results. It has been verified that the prediction model has an accuracy of 95% for the diameter and processing time of the electroporation micropores. The use of intelligent algorithms such as machine learning and artificial neural networks to solve complex nonlinear
problems in the field of practical engineering has obvious advantages. The model of this paper has certain guiding significance for future production.

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