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Research on ANN based on Simulated Annealing in Parameter Optimization of Micro-scaled Flow Channels Electrochemical Machining

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미세 유동채널의 전기화학적 가공 파라미터 최적화를 위한 어닐링 시뮬레이션에 근거한 인공 뉴럴 네트워크에 관한 연구

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Abstract In this paper, an artificial neural network based on simulated annealing was constructed. The mapping relationship between the parameters of micro-scaled flow channels electrochemical machining and the channel shape was established by training the samples. The depth and width of micro-scaled flow channels electrochemical machining on stainless steel surface were predicted, and the flow channels experiment was carried out with pulse power supply in NaNO3 solution to verify the established network model. The results show that the depth and width of the channel predicted by the simulated annealing artificial neural network with "4-7-2" structure are very close to the experimental values, and the error is less than 5.3%. The predicted and experimental data show that the etching degree in the process of channels electrochemical machining is closely related to voltage and current density. When the voltage is less than 5V, a "small island" is formed in the channel; When the voltage is greater than 40V, the lateral etching of the channel is relatively large, and the "dam" between the channels disappears. When the voltage is 25V, the machining morphology of the channel is the best.

Key Words : Micro-scaled flow channel, Neural network, Simulated annealing, Electrochemical machining, Prediction model, Parameter optimization

요 약 논문에서는 어닐링 시뮬레이션에 근거한 인공 뉴럴 네트워크를 구축한다. 미세 유동채널의 전기화학적 가공 파라미터와 채널 형태 간의 매핑은 샘플의 학습에 의하여 이루어진다. 스텐리스강 표면에 대한 미세 유동채널의 전기화학적 가공의 깊이와 넓이가 예측되고, 형성된 네트워크 모델을 입증하기 위한 NaNO3 해 내부의 펄스 전원공급기와 함께 유동채널의 실험이 진행된다. 결과적으로, “4-7-2” 구조를 갖는 인공 뉴럴 네트워크에 의한 어닐링 시뮬레이션으로 예측된 채널의 깊이와 넓이는 실험값에 매우 근접한다. 그 오차는 5.3% 미만이다. 예측된 데이터와 실험 데이터는 전기화학적 가공 과정에서의 에칭 규격이 전압 및 전류의 밀도와 매우 밀접한 관계가 있음을 보여준다. 전압이 5V보다 작을 때에는 채널 내에 “작은 섬”이 형성된다; 반면에 전압이 40V보다 클 때에는 채널의 측면 에칭이 비교적 크고 채널 사이의 “댐”은 사라지게 된다. 전압이 25V일 때 채널의 가공 형태는 최적이 된다.

주제어 : 미세 유동채널, 뉴럴 네트워크, 어닐링 시뮬레이션, 전기화학적 가공, 예측 모델, 파라미터 최적화

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1. INTRODUCTION

The electrochemical machining(ECM) is based on the principle of electrochemical anodic dissolution. The cathode "tool" is not in direct contact with the workpiece, and has no effect of "cutting force" and "cutting heat". There will be no residual stress on the workpiece surface and recast layer like laser machining. It can process metal materials which is difficult to cut , such as stainless steel, quenched steel and alloy. It has been continuously developed and applied in the processing of aeroengine blades, guns, gun barrel rifling and other parts[1-3]. Based on the regression model, Aakash et al. predicted the material removal rate and surface roughness in nickel base alloy ECM, and optimized the process parameters such as voltage, electrode gap and prop feed speed. The predicted results are helpful to improve the production capacity[4-11].

Electrochemical process knowledge covers a wide range of disciplines, many of which are stored as the experience of process design researchers. In addition, new processes and new technological achievements continue to appear, and the accumulation of process knowledge is also growing rapidly. The demand of researchers is not just for simple process retrieval. Researchers spend a lot of time and energy on the comparison and analysis of processing parameters knowledge, and then use the traditional experimental method for product iteration, which reduces the work efficiency. To solve these problems, the knowledge management of the electrochemical machining process is the way to improve the core competitiveness of research groups in the field of intelligent manufacturing[12-13].

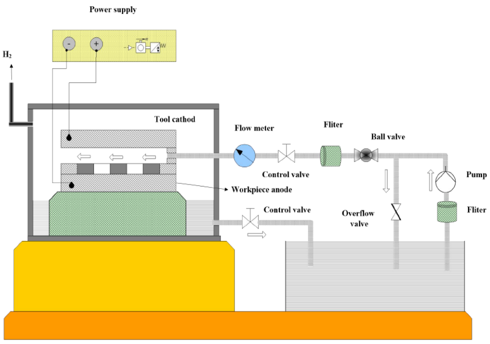
Electrochemical machining has a variety of processing processes corresponding to different materials and workpiece needs. Therefore, the establishment of a process knowledge management mechanism can promote the flow and integration between different processes. The research on the prediction of process parameters can help researchers jump out of the bottleneck of process research and help to screen the most appropriate process parameters, to shorten the number of orthogonal experiments of the workpiece and save the cost of process optimization, and accelerate the innovation of new processes.[14-16].

The remainder of the paper is structured as follows. Section 2 provides details about electrochemical machining method, back propagation neural network method and artificial neural network method based on simulated annealing algorithm. The network prediction results and test results are given in Section 3 and the paper ends with a conclusion in Section 4.

2. METHODS

2.1 Electrochemical Machining Method

As shown in Fig. 1, the self-developed micro-scaled flow channels ECM system is included electrolyte circulation system, metal double-layer fixture system and power control system.



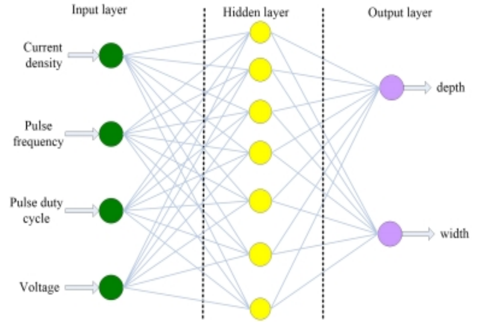
[Fig. 1] Micro-scaled flow channels ECM system

The internal area of the metal double-layer fixture system is made of plexiglass material, with good overall sealing and corrosion resistance, which is easy to be fixed on marble. The electrolyte inside the doublelayer fixture adopts the flow measurement method. The electrolyte flows through the flow channel with gentle cross-section change, and the speed and pressure change slowly. The flow field uniformity is good, which can prevent cavitation and is conducive to the design and forming of anode workpiece. The distance between anode and cathode is fixed at 4mm. The electrolysis control system adopts the single pulse power supply of rsnp-4050, which is more reliable than the general DC power supply.

2.2 Artificial Neural Network Model

In this paper, a back propagation neural network is used to predict the channel depth and channel width of micro-scaled flow channels ECM. It is a multilayer feedforward network composed of input layer, hidden layer and output layer. It has the characteristics of signal forward calculation and error back propagation.

In the optimization of micro-scaled flow channels ECM, four factors affecting channels forming are selected as the inputs of neural network, including current density *D*, pulse frequency *f*, voltage *U* and pulse duty cycle PD. The four components correspond to the input layer nodes respectively, and each generation represents an influencing parameter, which has different physical significance, the output terms of the artificial network are the depth dm and width wm of the flow channels. The artificial neural network structure is shown in Fig. 2.



[Fig. 2] Artificial neural network structure

3. RESULTS AND ANALYSIS

3.1 Sample pretreatment

Firstly, the samples were reduced. At the beginning of the processing of electroformed copper processing test samples, the samples similar to the expected experiment were selected, normalized with sigmoid function and the data of different dimensions were changed to [0, 1] or [-1, 1] for the input samples.

In this paper, the number of nodes in hidden layer of ANN and SAANN were evaluated, the impact of different number of nodes in the hidden layer on the network performance was detected through the same sample, the number of nodes was selected when it has the smallest relative error of the prediction result, and the relative error of the network is less than 0.53. The optimal structure of the single hidden layer network was determined as 4-7-2. The hidden layer has seven nodes. This structure had a good performance in network prediction.

"4-7-2" structure neural network includes the process of learning signal forward propagation and error signal back propagation. Input samples are input from the input layer, processed by each hidden layer, and transmitted to the output layer. Calculate the error between the output result and the expected output result, and enter the error back propagation stage. The error is transmitted back to the input layer through the hidden layer, and each layer modifies the weight of each unit according to the error signal. These two processes are repeated and the weights are constantly adjusted, which is the process of network model training and learning. The degree of error acceptance and the number of learning are often used to control the termination of training.

3.2 Model Prediction Results

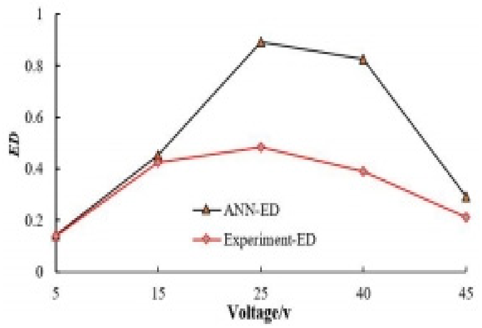
The trained SAANN prediction model was used to predict the results of micro-scaled flow channels ECM, and the process parameters were used as the input of neural network to predict the results of stainless steel micro-scaled flow channels ECM. The current density values were 12A15A, 19A, 22A and 28A, the pulse frequency values were 0.5kHz, 1.5kHz and 2kHz, the pulse duty cycle values were 40% and 60%, the output parameters comply with the law of actual processing, and the depth of micro-scaled flow channels was between 24.181~151.273μm, the width of flow channels was between 169.761~353.723μm, the depth and width of the flow channels vary significantly with the voltage and current density. The pulse size directly affected the processing time.

3.3 Experimental Verification

The stainless steel(SUS304) was selected as the material of micro-scaled flow channels during the ECM. And the input values of neural network were used as the initial values of experimental parameters. The depth and width of flow channels under neural network prediction and electrochemical machining were compared and analyzed.

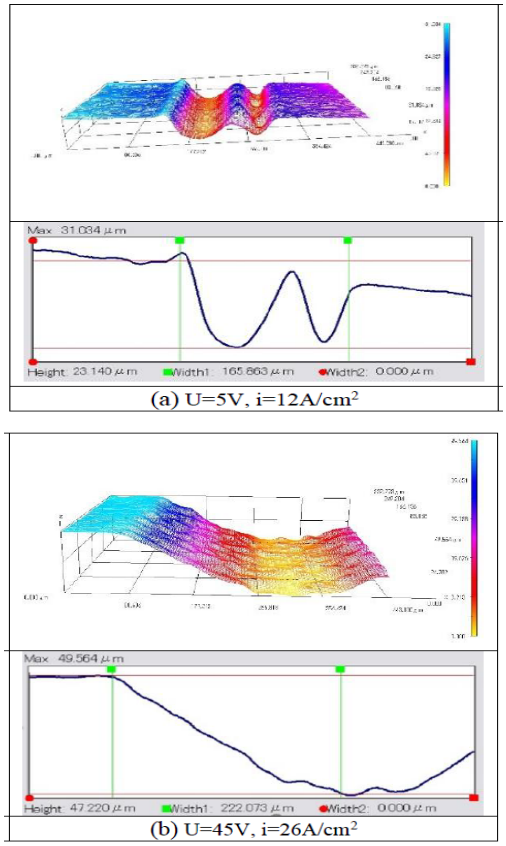
In this paper, the etching degree was introduced as the reference evaluation factor. The etching degree was defined as depth/width, which was used to further analyze the internal law of ECM process of flow channels. After processing, the width, depth and surface morphology of the workpiece were detected by SEM and Leica equipment, as shown in Fig. 4 and 5.

With the increase of processing voltage, the average current density increased. The rate of material removal in depth direction and width direction also increased. In this paper, it was evaluated by etching degree, as shown in Fig. 3.



[Fig. 3] Variation Trend of etching degree under different voltages

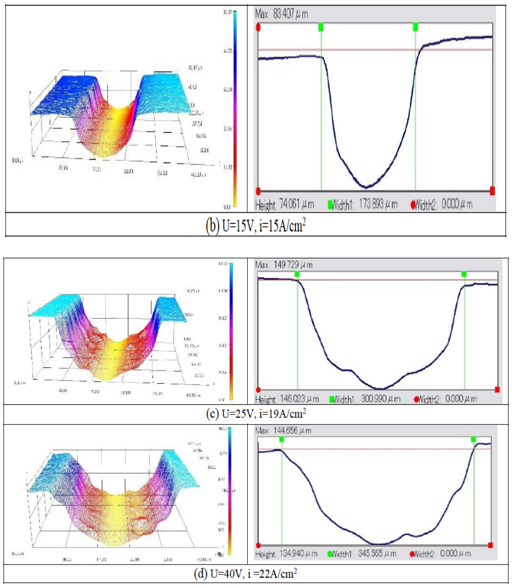
The morphology and cross-section in Fig. 4(a) are the results of ECM of the flow channel when the voltage is 5V. The image shows that when the processing voltage is too small, the "island" shape will appear in the flow channel in the image, which will affect the forming of the channel.



[Fig. 4] Morphology and section of channels

It means the processing voltage cannot be too small. The lateral etching of the channel was too fast with too large processing voltage, which is easy to cause the disappearance of the "dam" between the channels. It finally led to the failure of channel processing. When the processing voltage was 45V, the morphology and section of the flow channel are shown in Fig. 4(b), the depth of the channel was 47.22μm, the width of the channel was 2×222.073μm, and the processing speed in the channel width direction was too fast to form a qualified flow channel.

The processing voltages selected in the experiment in Fig. 5 are 15V, 25V and 40V, and the average current densities are 15A/cm2, 19.0A/cm2 and 22A/cm2. The morphology and cross section of the channel are shown in Fig. 4 (b) (c).



[Fig. 5] Morphology and section of flow channels

The average current density was used in this paper because the use of pulse power supply. The processing voltage increased from 5V to 25V, and the channel depth increased from 74.061μm to 146.023 μm. The improvement rate of machining depth was 0.972, while the improvement rate of flow channel depth predicted by artificial neural network was 0.97. Flow channel width increased from 173.893μm to 300.990μm. The improvement rate was 0.731, and the improvement rate predicted by artificial neural network was 0.71. It showed that the artificial neural network model could accurately predict the improvement rate of channel depth and width.

To sum up, the processing voltage is 25V, the current density is 19A/cm2 and the pulse duty cycle is 0.4, which are the optimal parameter combination. The prediction results of SAANN model and the morphology of processing test can be confirmed.

4. CONCLUSION

In this paper, an artificial neural network based on simulated annealing was constructed to optimize the process parameters of micro-scaled flow channel ECM on the surface of stainless steel. The experimental data show that the SAANN has excellent prediction ability, and the prediction error is within 5.3%. It can reduce the parameter selection time of micro-scaled flow channels ECM, so as to reduce the number of traditional orthogonal experiments and save the experimental costs. It is noteworthy that the experimenters need to use the field data with strong pertinence in ECM to train the network model in order to achieve better results.

The prediction results of SAANN and experimental results show that the pulse current density and voltage has a great influence on the depth and width of stainless steel flow channels. Under the same voltage, the pulse duty cycle is between 0.2 and 0.4, and the influence coefficient of pulse on machining results is less than 0.007. Therefore, in order to improve the machining effect of stainless steel micro-scaled flow channel, voltage and current density are important.

Due to the small amount of experimental data of ECM examples, it is not suitable to use the currently popular deep neural network learning to predict ECM. In the follow-up work, the research team will make every effort to collect and mine the experimental data of various machining examples, find more factors affecting micro-scaled flow channel ECM, and pay attention to the progress of small data learning and prediction, as well as being committed to the improvement of electrochemical machining process.

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〈관심분야〉

digital communication systems, Big Data