Improvement of Electroforming Process System Based on Double Hidden Layer Network

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이중 비밀 다층구조 네트워크에 기반한 전기주조 공정 시스템의 개선

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Abstract In order to optimize the pulse electroforming copper process, a double hidden layer BP (Back Propagation) neural network is constructed. Through sample training, the mapping relationship between electroforming copper process conditions and target properties is accurately established, and the prediction of microhardness and tensile strength of the electroforming layer in the pulse electroforming copper process is realized. The predicted results are verified by electrodeposition copper test in copper pyrophosphate solution system with pulse power supply. The results show that the microhardness and tensile strength of copper layer predicted by "3-4-3-2" structure double hidden layer neural network are very close to the experimental values, and the relative error is less than 2.32%. In the parameter range, the microhardness of copper layer is between 100.3~205.6MPa and the tensile strength is between 112~485MPa.When the microhardness and tensile strength are optimal,the corresponding process conditions are as follows: current density is 2A-dm-2, pulse frequency is 2KHz and pulse duty cycle is 10%.

Key Words : double hidden layer, BP neural network, electroforming, optimization, copper process

요 약 구리의 전기주조 공정을 최적화하기 위하여 이중 비밀 다층구조의 역전파 뉴럴 네트워크가 구성된다. 샘플 학습을 통하여, 구리 전기주조 공정 조건과 목표 특성 간의 함수관계가 정확히 성취되고, 구리 전기주조 공정 내에서 다층구조의 미세강도와 장력에 대한 예측이 이루어진다. 예측된 결과는 펄스 전원공급기를 장착한 구리 피로인산염 솔루션 시스템 내에서 구리의 전해석출 시험에 의하여 증명된다. 그 결과는 다음과 같이 나타난다. “3-4-3-2” 구조의 이중 비밀 다층구조 뉴럴 네트워크에 의하여 예측된 구리 다층구조의 미세강도와 장력은 실험값에 매우 근접하며 그 상대적 오차는 2.32%보다 작다. 주어진 파라미터의 범위 내에서, 구리의 미세강도는 100.3~205.6MPa이며, 장력은 112~485MPa 정도로 측정된다. 미세강도와 장력이 최적인 조건에서 그에 대응하는 공정 조건은 다음과 같다: 전류밀도는 2A·dm-2, 펄스 주파수는 2KHz, 펄스의 듀티싸이클은 10%이다.

주제어 : 이중 비밀 다층구조, 역전파 뉴럴 네트워크, 전기주조, 최적화, 구리 공정

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1. INTRODUCTION

In electroforming process, the method of deposited layer forming is special, which is used to prepare metal parts with special shape or molds with high precision requirements [1-3]. Electroforming process relies on the electrons from metal ions stacked on the cathode surface one by one, and its theoretical accuracy can reach the ion level. It is widely used in the preparation of micro structural parts with small and complex structure on the surface. Traditional electroforming technology has problems such as uneven distribution of electric field intensity, hydrogen evolution and difficult mass transfer at the microstructure of parts. The electroforming layer is prone to quality defects such as pinholes, pits and cavities, and the deposition thickness is uneven, which can not completely copy the whole microstructure, affecting the forming quality of microstructure parts [4,5]. When the complex structure is copied by DC power electroforming, the nodulation is easy to occur on the surface and edge of the electroforming layer. At the same time, the grain size and surface roughness of the deposited layer appear, and the performance index of the electroforming layer can not meet the actual demand. Through a large number of experimental studies, many researchers found that Electroforming with pulse power supply is an important means to improve the quality of deposited layer [6-8].

In pulse electroforming, the electrode process changes from DC process to periodic pulse process. The pulse power supply affects the electrode process, thus affecting the physical properties and quality of the deposited layer. Pulse electroforming can supplement the concentration of metal ions in the diffusion layer, significantly reduce the concentration polarization and produce higher electrochemical polarization, so as to refine the grain and improve the density of the deposited layer; The thickness of the diffusion layer is reduced due to the intermittent formation around the diffusion layer; Increasing the cathode limiting current density, the metal crystal morphology and growth mode during electroforming are closely related to the cathodic polarization overpotential. Increasing the overpotential can make the grain finer and the deposited layer compact. In pulse electroforming, the uniformity of the deposited layer is affected by the distribution of current density and the transmission of electrolyte components. Intermittent energization can buffer the ion concentration on the cathode surface, greatly reduce the difference in the thickness of the deposited layer caused by the uneven transmission of electrolyte components, and improve the uniformity of the deposited layer.

Yuan Xuetao obtained the grain size of deposits with fine appearance can only be refined down to about 100 nm by changing the pulse parameters[9]. Fafeng Xia used the pulse electrodeposition (PED) technique, which showed that the contents of AlN nanoparticles increased with density of pulse current and on-duty ratio of pulse current increasing[10]. S.A. Lajevardi investigated the effects of pulse electrodeposition parameters on the properties of nickel-titania composite coatings electrodeposited from a nickel Watts type bath[11-14].

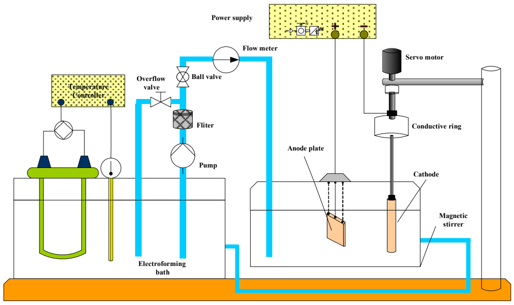
In the current electroforming research process, a large number of experiments need to be carried out to obtain the relationship between electrodeposition process parameters and coating properties, which greatly affects the efficiency of product development in experiment and industrial production, and therefore consumes a lot of manpower and time cost. Artificial neural network has good self-learning function and can efficiently find the optimal parameters of electroforming process. It is widely used in the fields of intelligent machining, signal processing and optimal combination[15].

In this paper, the optimal parameters of pulse electroforming copper process is studied. The mapping relationship between the input parameters and the output parameters of microhardness and tensile strength is established by using double hidden layer back propagation neural network. Through model training, the linear inseparable problem under the electroforming copper processing model is solved by using the multi-dimensional function mapping ability and self-learning ability of multi-layer perceptron. Finally, the process parameters of the optimal performance of electroformed copper are predicted[16].

2. ELECTROFORMING PROCESS SYSTEM

2.1 Copper Electroforming Method

The self-developed electroforming copper system is shown in the [Fig. 1], including electroforming liquid circulation system, electroforming liquid temperature control system, fixture system and power supply system. The anode plate is made of phosphor copper.The cathode shape is a metal tube with a diameter of 6mm and a length of 50mm, section of which is as shown in [Fig. 1]. The rest cathode immersed in the solution shall be insulated.The distance between anode and cathode was fixed with 40mm.



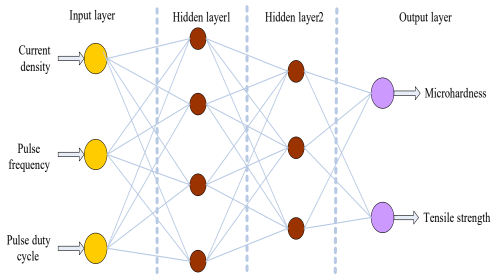
[Fig. 1] Schematic diagram of electroforming system

2.2 Double Hidden Layer BP Network Model

In this paper, the microhardness and tensile strength in copper electroforming process are trained and predicted based on BP neural network.Only increasing the number of nodes of single hidden layer can not improve the prediction ability of neural network for copper electroforming process parameters. In this paper, a method of adding a second hidden layer is proposed, which uses the multi-dimensional function mapping ability and self-learning ability of multi-layer perceptron. When dealing with the linear inseparable problem under the electroforming copper processing model, the double hidden layer BP neural network is superior.

BP neural network has the characteristics of signal forward calculation and error back propagation. The multilayer feedforward network composed of input layer, hidden layer and output layer is gradually optimized by back propagation algorithm, and the weight of each perceptron is continuously adjusted according to the minimum loss function until the training goal is reached.

In the network model of copper electroforming process parameter optimization, three parameters that most affect the results of copper electroforming are selected as inputs d, f and γ correspond to the nodes of the input layer respectively. The three components have different physical meanings with small correlation, which can be detected and extracted. Microhardness H_v and tensile strength Rm are selected as the output items of BP network. The double hidden layer network constructed in this paper is shown in [Fig. 2]. In BP network, the first hidden layer has 4 nodes and the second hidden layer has 3 nodes.



[Fig. 2] Double hidden layer network structure

3. EXAMPLE RESULTS AND ANALYSIS

3.1 Sample pretreatment

Firstly, the samples are reduced. At the beginning of the processing of electroformed copper processing test samples, 137 samples similar to the expected experiment are selected, normalized with sigmoid function, and the data of different dimensions are changed to [0,1] or [-1,1] as the input samples. ⟨Table 1⟩ shows some samples. Normalization can avoid the saturation of neuron output caused by too large continuous value and slow down the convergence speed. In this paper, it is transformed by equation (1).

$$x^* = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \quad (1)$$

x^* is the normalized sample, x is the original value, x_{min} and x_{max} are the minimum and maximum values respectively. In the forward propagation learning of the signal in the network, the difference between the output signal and the teacher signal was compared, the error signals of the output layer and the double hidden layer were inversely calculated according to the error value, and the corresponding weights were adjusted layer by layer.

3.2 Analysis of network model experiment results

Due to the lack of nonlinear mapping ability of single hidden layer network in electroforming copper process optimization, increasing the number of nodes of single hidden layer can not improve the performance of the network. In this paper, adding hidden layer can improve the mapping ability of the artificial network to the parameters such as current density d, pulse frequency f, pulse duty cycle γ, microhardness H_v and tensile strength R_m. The node design in the double hidden layer network needs to avoid over fitting or increasing the training time of samples.

In this paper, the trial-and-error method is used to determine the number of neurons in the double hidden layer. By detecting the network performance of different numbers of nodes in the double hidden layer for the same sample, the optimal number of nodes is obtained. Firstly, the trial-and-error experiment is carried out on the single hidden layer, and the optimal number of nodes in the network is 7, and the relative error of the prediction result is 0.112. Then eight groups of experiments are designed based on the characteristics of the double hidden layer network.

Based on the number of nodes in a single hidden layer, two principles should be followed in the construction of a double hidden layer: 1. The total number of nodes in a double hidden layer should not be greater than the number of nodes in a single hidden layer; 2. The number of nodes in the second hidden layer is less than that in the first layer. In ⟨Table 1⟩, The number of double hidden layer nodes in six groups of experiments is not greater than 7, and two groups of experiments with more than 7 nodes are set for comparison. According to the relative error of the combination of multiple nodes in the hidden layer in the prediction results, the structure of the double hidden layer network is determined as: 3-4-3-2. The first layer of the double hidden layer has 4 nodes and the second layer has 3 nodes. This structure has a good performance in the prediction of the network. The experimental results are shown in ⟨Table 1⟩.

〈Table 1〉 Network performance with different number of neurons

Number of nodes in h_1	Number of nodes in h_2	Network relative error	Running times /m
6	1	0.102	4.3
5	2	0.095	4.1
4	3	0.021	2.9
4	2	0.049	3.3
3	4	0.077	4.2
7	1	0.109	3.4
5	3	0.105	3.7
3	3	0.085	3.1

The running time in 〈Table 1〉 is the time when the network tends to be stable. Generally, when designing a more complex network, it is necessary to take the cross value of the network error change curve of the model in the training sample and the test sample. At this time, the error in the training sample tends to be smaller, while the error in the test set tends to be larger. If only the error value is considered, there may be over fitting, which performs well in the training samples and insufficient in the test samples, affecting the generalization ability of the model. There is no fitting phenomenon in this experiment, and the network performance is good.

3.3 Experimental verification

In the experiment of electroformed copper, the experiment was carried out according to the input parameters. Neural network prediction and physical experiments show that with the change of pulse current density, frequency and duty cycle, the microhardness and tensile strength of the electroforming layer have changed significantly, mainly in the following aspects:

(1) Neural network prediction and experiments show the effect of current density on microhardness and tensile strength. The microhardness of electroformed layer decreased with the increase of current density. When the average pulse current density is 2A·dm^{-2}, the microhardness of copper layer is the highest, reaching 202.7Mpa. When the average pulse current density increases to 4A·dm^{-2}, the microhardness of the copper layer decreases to 105.4Mpa. When DC power supply is used for electroforming, the microhardness of electroformed copper layer is lower than that of pulse current. When the average current density increases from 2A·dm^{-2}, the grain size becomes larger. According to the fine grain strengthening theory, the hardness of the material is inversely proportional to the grain size. Therefore, the microhardness of the copper layer will continue to decline.

(2)Neural network prediction and experiments show the effect of pulse frequency on microhardness and tensile strength. With the increase of pulse frequency, the microhardness of electroformed copper layer increases first and then decreases. When the pulse frequency is 0.5kHz, the minimum microhardness of electroformed copper layer is 106.4Mpa. As the pulse frequency continues to increase, the microhardness of the electroforming layer also increases, and reaches the peak at 2kHz.

(3) Neural network prediction and experiments show the effect of pulse duty cycle on microhardness and tensile strength. The microhardness of electroformed copper layer gradually increases with the decrease of duty cycle, and reaches to 202.7Mpa when the duty cycle is 20%. When the duty cycle is 20%, the surface morphology of the copper layer is the most smooth and flat, and the grain size is the smallest and uniform. According to the fine grain strengthening theory, the microhardness of the electroforming layer is the largest, and the results are consistent.

The tensile strength of the cast layer decreases with the increase of duty cycle. When other conditions are constant, when the duty cycle increases from 20% to 80%, the tensile strength of the electroforming layer decreases from 472Mpa to 353Mpa. The analysis shows that the change of duty cycle changes the grain size and microstructure of electroformed copper layer, resulting in the change of strength of electroformed copper layer, and its change trend is consistent with the change trend of grain size.

4. CONCLUSION

In this paper, The predicted results and experimental results of double hidden layer BP neural network can obtain the optimum tensile strength and microhardness of pulse cast copper. The conditions are as follows: current density is 2A·dm-2, pulse frequency is 2kHz and pulse duty cycle is 20%. Under these conditions, a uniform and dense copper layer can be obtained.

The relationship between electroforming copper process parameters and tensile strength and microhardness is nonlinear and complex, and there is no specific correlation expression. Double hidden layer BP neural network has good nonlinear mapping ability and generalization ability, and has great advantages over other empirical formula methods. It carries out training and learning by optimizing the number of nodes in the double hidden layer of the network, and identifies the complex relationship between the input and output of electroforming copper process, which provides an innovative way to solve the optimization problem of electroforming copper process parameters.

Double hidden layer BP neural network can comprehensively consider the influence of electroforming copper process parameters on deposition results. The predicted tensile strength and microhardness are close to the actual experimental results, and the training accuracy is high. It has a good popularization ability in the field of intelligent electroforming.

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