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Estimating Of Etchant Copper Concentration In The Electrolytic Cell Using Artificial Neural Networks

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Abstract

In this paper, Artificial Neural Networks (ANN), which are known for their ability to model nonlinear systems, provide accurate approximations of system behavior and are typically much more computationally efficient than phenomenological models are used to predict the etchant copper concentration in the electrolytic cell in terms of electric potential, operating time, temperature of the electrolytic cell , ratio of surface area of poles per unit volume of solution and the distance between poles. In this paper 350 sets of data are used to trained and test the network.. The best results were achieved using a model based on a feedforword Artificial Neural Network (ANN) with one hidden layer and fifteen neurons in the hidden layer gives a very close prediction of the copper concentration in the electrolytic cell.

***Key Words*: Artificial Neural Network, Simulation, Copper metal regenerated , Electrolytic cells**

تحديد تركيز نحاس الحفر في الخلية الالكتروليتية باستخدام الشبكات العصبية

الخلاصة

يستخدم هذا البحث شبكة الذكاء الصناعي والمعروفة بقابليتها على تكوين موديل للأنظمة الغير خطية، وإعطاء تقريب دقيق لسلوك النظام وتخمين مثالي وبشكل أكثر كفاءة من الموديلات الظاهرية المنطقية حيث يستخدم هذا البحث الشبكة لتخمين تركيز نحاس الحفر في الخلية الالكتروليتية بدلالة كل من الجهد الكهربائي وزمن التشغيل ودرجة حرارة الخلية الالكتروليتية والنسبة بين المساحة السطحية الاقطاب وحجم المحلول والمسافة بين الاقطاب. تم في هذا البحث استخدام 350 من مجموعة البيانات لتدريب واختبار الشبكة. وقد تم الحصول على أفضل النتائج باستخدام موديل يعتمد على شبكة الذكاء الصناعي ذات الانتشار الأمامي تبنَّت وتدربت بخوارزمية الانتشار العكسي ذات الطبقة المخفية الواحدة والخمسة عشر خلية عصبية في تلك الطبقة لتعطي تخمينا قريبا جدا لتركيز نحاس الحفر في الخلايا الالكتروليتية.

الكلمات الدالة: شبكة الذكاء الصناعي ، المحاكاة ،استعادة معدن النحاس، الخلايا الالكتروليتية.

Nomenclature

A:	Ratio of surface area of poles per unit volume of solution (a)	
Ai:	Actual etchant copper conc.	(g/l)
N:	Number of samples	
Pi:	Predicted etchant copper conc.	(g/l)
R^2:	multiple coefficient	
RMSE:	Root mean square error	
t:	Operating time	(min)
T:	Temperature	(°C)
V:	Electric potential	(Volt)
X:	Distance between poles	(cm)

Introduction

A simulation model for the prediction of etchant copper concentration in the electrolytic cell involved complex non-linear relationship between the operating conditions. Computers are an integral part of day to day activities in engineering design and engineers have utilized various applications to assist them to improve their design [1]. Artificial Neural Network (ANN) mimics some basic aspects of the brain functions. It is based on the neural structure of the human brain, which processes information by means interaction between many neurons[2]. Artificial Neural Networks (ANNs) are tools for building models from data. Simulating the function of the human nervous system they are essentially an applied mathematical technique, bearing a related biological terminology. They can be implemented whenever there is a vague or even unknown relationship between input and output data, though there is an adequate supply of data illustrating this relationship. Artificial Neural Networks are supposed to be able to handle complex multivariate relationships, non-deterministic or non-linear problems, even enter the field of fuzzy logic. In addition, they offer fast speed of analysis, objective viewpoint, the ability to generalize and to extrapolate beyond initial data range and provide rather simple and quick update processes hidden behind complicated in most cases algorithms which undertake the role of their theoretical setting. Thus , they have already been used for forecasting as well as for other predictive and classifying tasks[3] .Over the last few years, Artificial Neural Networks were applied in the chemical engineering. Ashfaq S. and Al-Dahhan M.[4] predicted the overall gas holdup in the bubble column by using the Artificial Neural Network. You , X .Y and Yang, Z .S.[5] using ANN to estimate the relative tray efficiency of sieve distillation trays. Fontes C.[6] predicted the oil content in wax in an oil dewaxing by development of ANN. The Artificial Neural Network, is not fully studied and explored in the field of electrochemical system, provides an alternative method for modeling complex systems [4]. Due to the complexity of finding a simulation model for this system, an alternative ANN approach was employed to model and predict the etchant copper concentration in the electrolytic cell. Artificial Neural Network does not require a prior fundamental understanding of the process or phenomena being modeled, thus, eliminating the need for numerous mathematical relationships. The architecture of the network used in this research was Feed Forward Artificial Network (FFAN) and the training of the network was done using Back Propagation Neural Network (BPNN) algorithm. This research developed ANN model using adequate number of training points obtained from the experimental study [7].

Artificial Neural Network (ANN) Structure Overview

The Artificial Neural Networks structure are borrowing from biological neural systems. It consist of nodes, or processing elements [PEs], each of which has an input, a body and an output. These nodes, organized in layers of the same functionality, are interconnected and produce a final output for the whole network. Each node receives weighted inputs, serving to simulate the role of biological synapses, either from original data or from other nodes inside the network. Also, inside every node there has been a single threshold value embedded to simulate the role of the biological"firing threshold" . This value is compared to the sum of the weighted input, so as to determine the activation, or inhabitation , of the node . The activation signal is then passed to transfer function to form the overall output of the neuron. The out put is in turn transferred to various weight links leading to other neurons of the net, such as that a practically unlimited number of nodes can be linked together to form a network of processing elements. This network is characterized by the presence of layers, each of which consists of nodes, typically an input layer, an output layer, in between, one ore more hidden intermediate layers of processing elements. The flow of the signals between the layers ranges from the feedforword structure where the signals flow from the input layer to any hidden layers reaching eventually the output layers, to the recurrent structure where nodes from one layer are linked to nodes from previous layers. Thus the complexity of the network increases .Furthermore , the structure of each node , as related to the transfer function applied to the weighted sum of its inputs, may not be the same ,providing a high versatile system with which to manipulate the input data[8]. Though a number of different kinds of neural networks exist, feedforward neural networks with one hidden layer have been focused. The function of the hidden layer is to process the information from the input layer. The hidden layer is denoted as hidden because it contains neither input nor output data and the output of the hidden layer generally remains unknown to the user. The feedforward network with one hidden layer is one of the most popular kinds of neural networks[5].

Methodology

The following steps were carried out in the development of ANN-based model used for the prediction of the etchant copper concentration in the electrolytic cell.

Regeneration Copper Etching Solution

The possibility of cutting any material with a chemical liquid is dependent first upon the availability of a chemical solution, generally known in this paper as (etchant), which will have a corrosive action on that material. Etchants are now available which give a controlled cut into practically every known material-event those which were developed primarily for their corrosion – resisting properties[9]. A solution of ammonium chloride (NH_4Cl) and copper sulphate ($CuSO_4$) which is called etchant is placed in the tank of etching machine. Etchant solution is pumped in a spray form to remove copper metal from printed circuit board (P.C.B) which is made of copper sheet. After many uses of etchant solution in etching copper, the concentration of copper is increased continuously. When it reaches 180 to 190 g/l, the etchant solution cannot satisfy the standard requirement, thus it is thrown away and replaced by a fresh solution[7]. Most etching processes can be reversed, so that by reaction similar electroplating processes which are defined as the electrodeposition of an adherent metallic coating upon an electrode for the purpose of securing a surface with properties or dimensions different from that of the basic material [10]. Or by the use of the precipitation, for example, the metal removed during the basic chemical milling operation can be recovered, or at least the metal content of the etchant can be significantly reduced [11]. Electrolytic recovery techniques can be traced to precursor of modern electrochemistry – electrogravimeteric determinations[12].

The database used in this study was taken from the results of experimental work [7]. 350 sets of data adapted to train and test the ANN model. The data gathered were values of the following variables: electric potential (V), operating time (t), temperature of the electrolytic cell (T), ratio of surface area of poles per unit volume of solution (a) and the distance between poles (X) they are used as input parameters to predict the etchant copper concentration in the electrolytic cell (the only output parameter).

Normalizing the Raw Data Collected

Generally, majority of the effort in developing a neural network model into collecting data and preprocessing them appropriately. The standard process is to normalize the raw data. Here, the requirement is that the inputs to each input processing elements should be in the between -1.0 to 1.0, inclusive and the output to each output processing elements should be between -1.0 to 1.0. Normalizing the raw data avoids numerical overflows due to very or small weights [6]. The transformation of actual variables (X,Y) to normalized variables (U,S) is given below :

$$U_i = \frac{\log(X_i / X_{\min})}{\log(X_{\max} / X_{\min})} \quad \text{………..….(1)}$$

$$S_k = \frac{\log(Y_i / Y_{\min})}{\log(Y_{\max} / Y_{\min})} \quad \text{……..… (2)}$$

Where :

i and k are the input and output neurons of the ANN structure respectively .

X_i : are the values of raw input variables from experimental work which represented by five variables (electric potential (V), operating time (t), temperature of the electrolytic cell (T), ratio of surface area of poles per unit volume of solution (a) and the distance between poles (X))

Xmin : is the minimum value of each input variable in the experimental work as

given below :

X_1(min) : min. value of voltage = 5 volt

X_2(min) : min. value of operating time = 2 minute

X_3(min) : min. value of temperature=15 ^{0}C

X_4(min) : min. value of the ratio of surface area of poles per unit volume of solution = 0.0126

X_5(min) : min. value of the distance between poles = 1 cm

Xmax : is the maximum value of each input variable in the experimental work as

given below :

X_1(max) : max. value of voltage = 13 volt

X_2(max) : max. value of operating time = 6 minute

X_3(max) : max. value of temperature = 55 ^{0}C

X_4(max) : max. value of the ratio of surface area of poles per unit volume of solution = 0.029

X_5(max) : max. value of the distance between poles = 4 cm

Y_i : is the value of raw output variable in the experimental work which represented by the etchant copper concentration in the electrolytic cell.

Ymin : is the min. value of output variable (copper concentration) = 30 g/l

Ymax : is the max. value of output variable (copper concentration) = 194 g/l

U_i : are the normalized values of the five input variables which are introduced to the network .

S_k : is the normalized value of the output variable (copper concentration) from the network.

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ANN Modeling of Electrochemical System

A Feed Forward Artificial Neural Network (FFNN) trained by back propagation, is widely used based on the complexity of the problem and the size of the database, the number of hidden layer and the neurons within each hidden layer, can be varied, Fig. (1) shows a three layer ANN structure with five inputs, one hidden layer with fifteen neurons, and one output. The input layer that distributes the inputs to the hidden layer does not have any activation function. Mathematically the network computes; the ANN structure as shown in Fig. (1). The basic structure of this type of neural network is described by the following equations. The various layers are interconnected to each other by a sigmoid (S-Shape) function through the fitted parameters w_{ij} , w_{jk} in the following manner,

$$S_k = \frac{1}{1+\exp[-\sum_{j=1}^{J+1} w_{jk} H_j]} \quad ....(3)$$

and

$$H_j = \frac{1}{1+\exp[-\sum_{i=1}^{I+1} w_{ij} U_i]} \quad ......(4)$$

Where : i , j, k indicate the input, hidden and output neurons of the ANN structure, respectively. H_{J+1} and U_{I+1} (Figure (1)) are the bias constant. w_{ij} and w_{jk} are weighting parameters [6],which are shown in Table (1).

The Training of the Network

After defining the structure of ANN model, data are then collected and fed to the model. The network is trained to recognize the relationship between the input and the output parameters. The input layer distributes the inputs to the hidden layer. The lines connecting the neurons represent the weights. At the beginning of trainings, the weights of the network are randomly chosen. For a fast convergence, the initial weights are in the range of (-1 , 1). As the training procedure starts, an algorithm to minimize the difference between the network predicted and the desired output adjusts the network parameters, such as the weights. The back propagation algorithm is used for this purpose since it is one of the most popular and extensively used algorithm for network training. By using back propagation, the network learns through an iterative procedure, involving two steps performed many times. First the examples of training data shown to the network are passed forward to the output layer to compute the errors at the output. The second step works backward through the network. The errors at the output layer are propagated backwards through the network and the weight allocated to each neuron connection are adjusted to minimize the error in the output data. Table (1) shows the weights used in the ANN model and the weights of the bias. Using this technique it is possible for the network to become trapped a local minima. For this reason, a supervised training method was used [5].

Testing Stage

In order to understand whether an ANN is making good predictions, test data that has never been presented to the network are used and the results are checked at this stage. The statistical methods of root mean square error (RMSE), the coefficient of multiple determination (R^2) values have been used for making comparisons [13,14]. These values are determined by the following equations:

$$RMSE = \left[\frac{1}{n}\sum_j \left(a_j - p_j\right)^2\right]^{\frac{1}{2}} \quad ....(5)$$

$$R^2 = 1 - \left[\frac{\sum_j \left(a_j - p_j\right)^2}{\sum_j \left(p_j\right)^2} \right] \quad \text{..........(6)}$$

Where :(p) is the predicted value, (a) the actual value and (n) the number of samples.

Results And Discussion

ANN of BPNN learning algorithm was used in the prediction of the etchant copper concentration in the electrolytic cell in terms of electric potential (V), operating time (t), temperature of the electrolytic cell (T) , ratio of surface area of poles per unit volume of solution (a) and the distance between poles (X). Two kinds of ANN models are chosen to train and test here. One model consists of an input layer of five input neurons corresponding to the five input parameters, one hidden layer and an output layer of one neuron representing the output parameter. Another model was the same structure except having two hidden layers. By comparing the results of ANN models, which have different number of neurons in each hidden layer, the optimal ANN structure can be obtained and this can be done by applying the backpropagation algorithm in the matlab program [15]. The training data, which were concretely selected, consisted of 300 patterns. Sufficient data (50 patterns) were used as test sets as. It is essential to have enough data as training and testing sets to train and evaluated the performance of the network effectively. The time of convergence depended on the number of processing elements in the hidden layer.

Determination of the optimal ANN Structure

Table (2) shows the results of training and testing ANN model with one hidden layer. In this Table, 5-i-1 represents the ANN model with five input neurons, i neurons in the hidden layer and one output neuron. The results indicate that the average percentage error decreases when the number of hidden layer neurons changes from 5 to 15 or from 17 to 15 .It is concluded that ANN structure (5 – 15 – 1) is the optimal one. In table(3) , (5 – i – j – 1) represents the ANN model with five input neurons, i and j hidden layer neurons respectively for the first and second hidden layer and one output neuron .When the number of neuron in the first hidden layer is more than 12 , the average percentage error degreases to minimum but the connection weights are large .Thus needs a much longer time for training .It is not economic and will not adopted as optimum ANN structure here. Two hidden layer ANN network, which spends comparable training time as the optimal one hidden layer ANN (5–15–1), shows no improvements comparing to that with one hidden layer. The comparisons of experimental results with the ANN predictions have been depicted in terms of percentage error for testing set of experiments. From Table (4) it is evident that for our set of data the neural network predicts the etchant copper concentration in the electrolytic cell nearer to the experimental values. In the prediction of the etchant copper concentration values in the electrolytic cell the average errors for ANN is found to be as 4.63 %.The average *RMSE* was found to be as 0.6326. The value of the multiple coefficient of R^2 between experimental results and ANN prediction is obtained as 0.9976. This value showed that ANN model fits well with the experimental results. Fig. (2) illustrates the ANN predictions against the experimental results. The training of the neural network was performed with an allowable error of 0.042 (sum of squared error over the output neurons). The learning behavior of this particular network is shown in Fig.(3). We can study the effect of electric potential, time, temperature, surface area of electrode and the distance between the electrodes on the copper concentration in the electrolytic cell solution by introducing the input variables which are not found in the experimental work to the optimal ANN model after training and testing it to show how the value of copper concentration obtained from ANN model behaves with that which obtained from experimental work.

The Effect of Electric Potential and Time on ANN model behavior

Fig.(4) shows the effect of electric potential on the copper concentration in the electrolytic cell solution for different temperatures. We noticed that the relationship between the electric potential and copper concentration is inversely linear proportional. The effect of time on the on the copper concentration is graphically shown in Fig.(5). It is clear that the copper concentration is inversely proportional with time and the relationship between time and copper concentration is not linear, however it is represented by curve of third order, i.e. the influence of time is more sensible than the electric potential. It can be interpreted as flows: If the voltage passes through the electrode is little, the metal ions is balanced slowly on cathode electrode, producing crystal kernels on the electrode surface with slight quantities. When this process continues , i.e. the time of passing the electric potential is increased , the deposited metal on the cathode surface becomes like big rough crystals and the speed of forming the crystal is increased by increasing the current density. If the electrical current passes through the electrode is more than the diffusion current , the metal deposited on poles is accompanied by rising hydrogen gas which makes the metal deposition is spongy with a lot of pores [16] Experimental data in Figs. (4 & 5) at a temperature of 25 ^{0}C are in solid symbols. Testing data at the intermediate conditions of a temperature 25 ^{0}C and at temperatures (20 and 40 ^{0}C) are on three curves. ANN testing and prediction are almost similar with that of experimental results. It can be seen on these Tigures that ANN is able to predict accurately the values of copper concentration at other testing conditions (T= 20 and 40 ^{0}C).

The Effect of Temperature on ANN model behavior

Fig. (6) illustrates the effect of temperature on the copper concentration in the electrolytic cell at different voltage .It is observe that at temperature lower than 15 ^{0}C the copper concentration decreases to less than (65 g/l), while at a temperature higher than 15 ^{0}C the copper concentration increases until it reaches a maximum at (26 to 30 ^{0}C) . After this range, the copper concentration decreases again. The diffusion of copper ion in the electrolyte is increased in the direction of the cathode electrode by increasing the temperature of the solution and this cause increases the rapidity of crystal formation, these crystal are big and rough. An increase of temperature has a good effect to reduce the over voltage of hydrogen on the cathode, which may increase rising this gas in the same time of deposition of metal on the electrode[7,16]. Fig.(6) shows that ANN model was able to predict the copper concentration at different electrolytic cell voltage which are not found in the experimental data. It is noted that ANN testing and prediction values are in the same trend behavior with that of experimental results.

The Effect of Surface Area of Electrode and The Distance Between Them on ANN model behavior

The relationship between the ratio of the surface area of electrode per unit volume of solution and copper concentration in the electrolytic cell is inversely proportional as shown in Fig.(7). Whenever the surface area of electrode (cathode) is increase, the space of deposition will be large, causes reducing in the fighter or mutual composition between ions to be deposit on the exposed surface area of cathode. The influence of the distance between electrodes is very small and can be neglected .In general, most electrolytic cells are built with anodes and cathodes quite close together (about inch apart). With this arrangement, the solution between the electrodes is kept effectively stirred by the evolution of hydrogen from the cathode surface[7,17]. The ANN model trend shows in fig.(7) is in agreement with the experimental results

Conclusions

In this study, the modeling of the effects of electric potential, operating time, temperature of the electrolytic cell, ratio of surface area of poles per unit volume of solution and the distance between poles on the etchant copper concentration in the electrolytic cell depending on various processing parameters have been presented. An ANN-based approach has been suggested and successfully implemented. The copper concentration values predicted by ANN model were found to be very close to the values obtained from experimental study. The average *RMSE* was found to be as 0.6326 and the value of the multiple coefficient of R^2 between experimental results and ANN prediction is obtained as 0.9976. It has demonstrated that the ANN model is a network with one hidden layer and fifteen neurons. It may be concluded that the ANN may be used as a good alternative for analysis of the effects of operating conditions on etchant copper concentration in the electrolytic cell. The advantages of the ANN compared to classical method are speed , simplicity and capacity to learn from the experimental study.

References

1. Durmus ,H. K., Ozkaya ,E., Meric ,C., Materials and Design, 27 (2006), 156–159.

2. Perzyk , M., Kochanski, A.W., Journal of Materials Processing Tech-nology, 109 (2001), 305–307.

3. Wagner, B. Misra, M. " Understanding Neural Networks Statistical Tolls " The American statistician , 50 , 4 , 1996 , 284-293.

4. Ashfaq S., Al - Dahhan M., "Development of an artificial neural network correlation for prediction of overall gas holdup in bubble column reactors, " Chemical Engineering and Processing , 42, P.599-600, 2003.

5. You , X .Y and Yang , Z . S., " Estimating the relative tray efficiency of sieve distillation trays by applying artificial neural networks " Chen. Biochem. Eng. Q., 17 (2), 153-158,2003.

6. Fontes C. and Guimaraes P. " Development of an artificial neural network model for predicting oil content in an oil dewaxing" ,2nd Mercosur Congress on Chemical Engineering, 2007.

7. Salih, M.I.., " Regeneration of copper etching solution " , M.Sc. , Thesis , University of Tikrit , 2001 .

8. Hewitson, B.C. and Crane , R.G., "Neural Net : Application in Geography ".Kluwer Academic Publishers, Dordrecht. 1994.

9. Beck, T. R. " Kinetic and mass transfer processes in electrolysis copper plating ",Application of polarization measurement in the control of metal deposition , USA , 1984 , P. 158 .

10. Loenheim and Fredrick, " Electroplating " , New York ; McGraw Hill , 1973.

11. Harris, W. T. , " Chemical milling , The technology of cutting material by etching " , Great Britain : Oxford University , 1976.

12. William, B., Inc , A.S. , Dibari ,G. A. ,"Testing of metallic and inorganic coatings " Chicago , 1986.

13. Nalbant M., Gokkaya H., Toktas I., Sur G. , Robotics and Compute Integrated Manufacturing, 2008, doi:10.1016/j.rcim.2007.11.004

14. Arcaklýoglu E. ,. Energy Res., 28 (2004), 1113–1125

15.Demuth H. , Beale M. , " Neural Network Toolbox for Use with Matlab " Version 3.0 , 1998.

16. Zee J. , White R.E. , Electrochemical Soc., Vol.133 , 1986 , P.5087

17. Clapper T.W. , Gale W.A. , " Encyclopedia of Chem. Technology. " Vol. 5, 1978 , P.50.

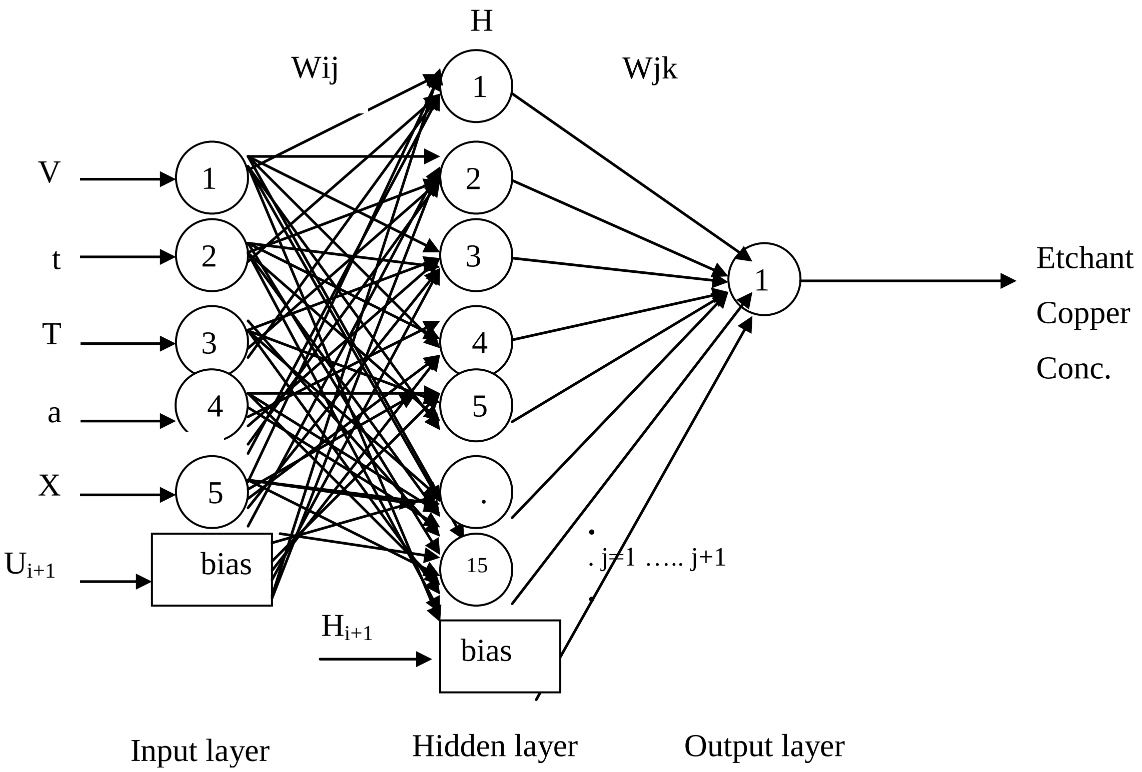

Fig. (1) Architecture of the three – layered feed forward neural network with single hidden layer.

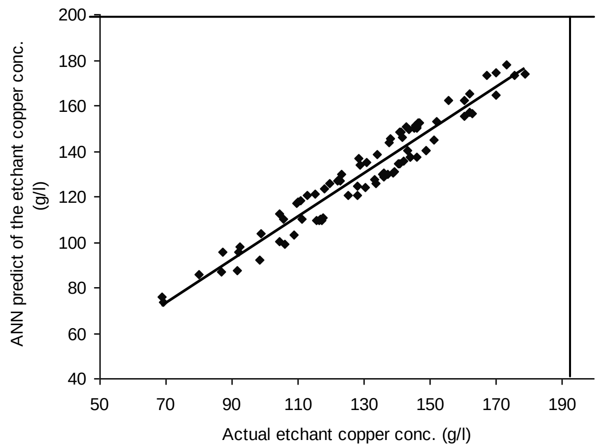

Fig.(2) Actual etchant copper concentration against the ANN predict of the etchant copper conc.

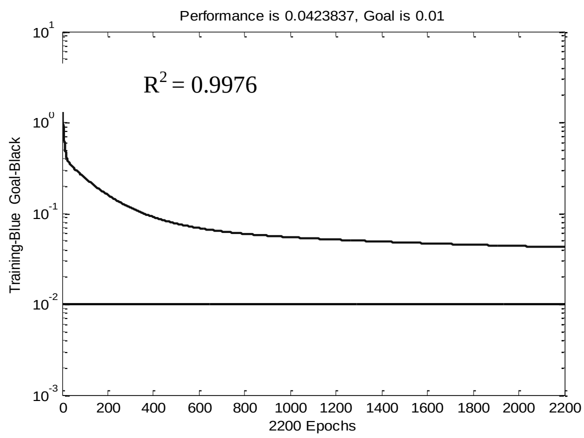

Fig.(3) Learning behavior of ANN model

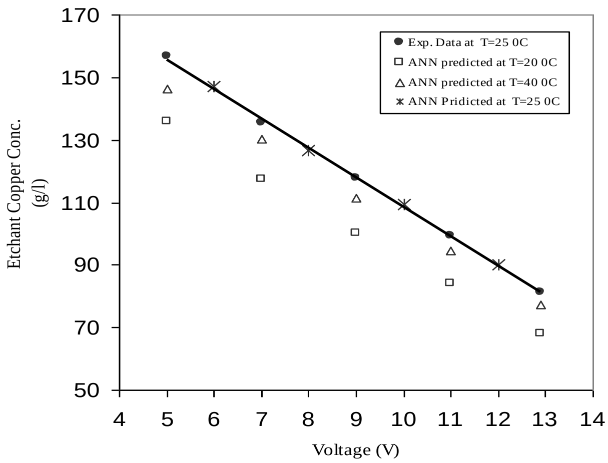

Fig.(4) Variation of Etchant Copper Concentration with Electrolytic Cell Voltage

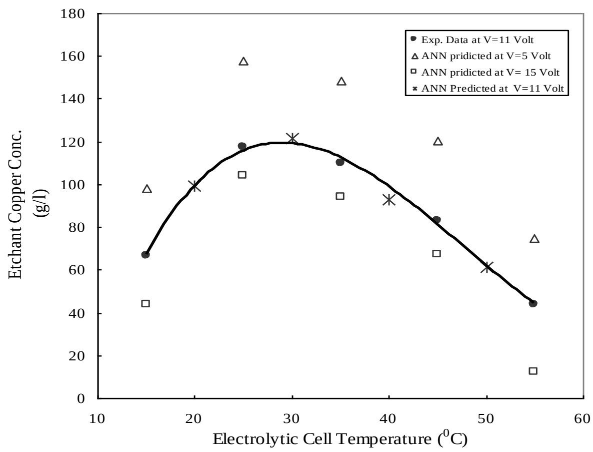

Fig.(6) Variation of Etchant Copper Concentration with Electrolytic Cell Temperature

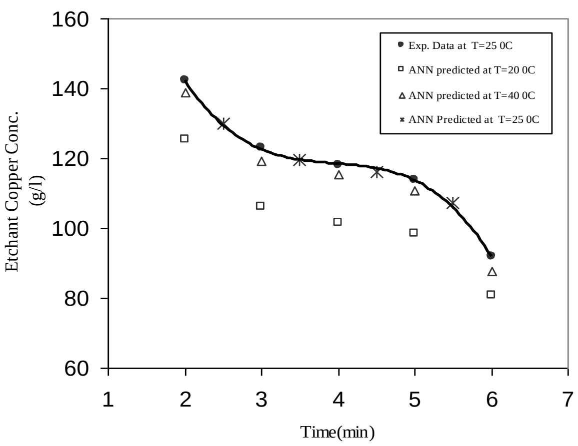

Fig.(5) Variation of Etchant Copper Concentration with Time

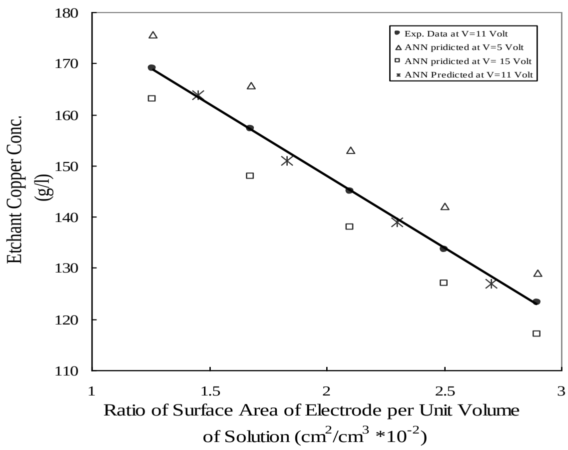

Fig.(7) Variation of Etchant Copper Concentration with Ratio of Surface Area of Electrode per Unit Volume of Solution (cm^2/cm^3*10^{-2})

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Table (1): The weights parameter used in the ANN model with one hidden layer and fifteen neurons.

Wij	1	2	3	4	5	6	7
1	-14.007	-1.221	0.128	3.207	36.941	0.299	-0.467
2	1.195	-0.610	-0.016	6.708	28.291	-14.680	-0.355
3	1.703	-24.360	-1.044	-6.997	0.309	-0.137	1.341
4	-1.053	-0.450	0.603	-6.487	-79.235	-0.171	-0.194
5	-0.346	4.030	-2.287	-16.294	20.690	-0.065	1.472
U_{i+1}	13.701	-11.812	2.619	-11.482	-23.841	-8.194	0.918
Wjk	1	2	3	4	5	6	7
1	-0.080	-0.370	36.929	0.010	0.012	0.251	-23.928

Table (1):Continued

Wij	8	9	10	11	12	13	14	15	
1	0.129	9.066	2.213	0.460	-1.315	-0.020	0.451	-2.134	
2	-0.017	52.140	0.271	0.345	0.075	13.011	0.335	-1.102	
3	-0.992	-15.586	0.264	-1.475	0.151	0.036	-1.627	-1.112	
4	0.724	-8.137	0.030	0.191	-0.025	0.114	0.190	-9.011	
5	-2.034	8.366	-0.020	-1.491	0.006	-0.005	-1.509	14.723	
U_{i+1}	2.497	4.004	2.178	-0.901	3.437	-7.213	-0.878	-3.764	
Wjk	8	9	10	11	12	13	14	15	H_{i+1}
1	-37.511	0.013	-0.421	-45.851	19.580	-0.182	22.081	0.132	-18.345

Table (2):The results of training and testing ANN model with one hidden layer.

ANN structure	Avg. (%) error for training data	Avg. (%) error for testing data
5 – 5 – 1	13.1	12.72
5 – 6 – 1	12.8	12.1
5 – 7 – 1	10.5	9.9
5 – 8 – 1	9.78	9.6
5 – 9 – 1	8.43	8.3
5 – 10 – 1	7.23	7.05
5 – 11 – 1	7.1	6.78
5 – 12 – 1	6.73	6.51
5 – 13 – 1	5.57	5.23
5 – 14 – 1	5.1	4.9
5 – 15 – 1	4.8	4.63
5 – 16 – 1	5.7	5.43
5 – 17 – 1	6.4	5.92

Table (3):The results of training and testing ANN model with two hidden layer.

ANN structure	Avg. (%) errorfor training data	Avg. (%) error for testing data
5 – 5 – 4 – 1	11.23	11.1
5 – 6 – 5 – 1	9.87	9.57
5 – 7 – 5 – 1	8.71	8.43
5 – 7 – 6 – 1	6.13	6.02
5 – 8 – 6 – 1	6.09	5.95
5 – 8 – 7 – 1	5.92	5.78
5 – 9 – 8 – 1	5.83	5.62
5 – 9 – 7 – 1	4.7	4.53
5 – 10 – 9 – 1	5.56	5.42
5 – 11 – 10 – 1	6.67	5.52

Table (4):Sample testing data introducing to the ANN with one hidden layer and fifteen neurons in this layer for prediction of the etchant copper conc.(g/l) in the electrolytic cell befor normalized. (Note: only 19 out of 84 patterns are shown)

Exp. No.	Electric potential (V) Volt	Operation time (t) Minute	Temperature of the electrolytic cell (T) ^0C	Ratio of surface area of poles per unit volume of solution (a)	The distance between poles (X) cm	Measured etchant copper conc. (g/l)	ANN			
							Predicted etchant copper conc. (g/l)	Error %	RMSE	R^2
1	7	6	45	0.025	2.5	104.2	112.7	8.16	0.927	0.9943
2	9	6	45	0.025	2.5	98.6	92.3	6.39	0.687	0.9953
3	11	6	45	0.025	2.5	91.5	87.8	4.04	0.404	0.9982
4	13	6	45	0.025	2.5	68.8	75.8	10.17	0.764	0.9915
5	5	3	45	0.029	2.5	146.7	152.4	3.89	0.622	0.9986
6	7	3	45	0.029	2.5	128	124.5	2.73	0.382	0.9992
7	9	3	45	0.029	2.5	122.4	127.5	4.17	0.556	0.9984
8	11	3	45	0.029	2.5	115.4	109.3	5.29	0.666	0.9969
9	5	4	45	0.029	2.5	143.9	137.6	4.38	0.687	0.9979
10	7	4	45	0.029	2.5	125.3	120.5	3.83	0.524	0.9984
11	9	4	45	0.029	2.5	119.6	125.8	5.18	0.676	0.9976
12	13	6	45	0.029	2.5	69	73.8	6.96	0.524	0.9958
13	5	3	25	0.0168	3.75	169.9	164.8	3.00	0.556	0.9990
14	7	3	25	0.0168	3.75	151.3	144.8	4.30	0.709	0.9980
15	9	3	25	0.0168	3.75	145.7	151.4	3.91	0.622	0.9986
16	11	3	25	0.0168	3.75	138.6	130.2	6.06	0.917	0.9958
17	13	6	25	0.0168	3.75	92.3	98.2	6.39	0.644	0.9964
18	5	2	35	0.021	3.75	178.6	173.7	2.74	0.535	0.9992
19	7	2	35	0.021	3.75	175.5	173.2	1.31	0.251	0.9998
							Average RMSE= 0.6326 Average R^2 = 0.9976 Average Error =4.63 %			