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Predictive Modeling of Copper in Electro-deposition of Bronze Using Regression and Neural Networks

K. Subramanian,[1,*] V.M. Periasamy,[2] M. Pushpavanam,[3] K. Ramasamy[1]

[1]*A.C. College of Engineering and Technology, Karaikudi 630 004, TN, India*
[2]*B.S.A.Cresent Engineering College, Vandalur, Chennai 600 048, TN, India*
[3]*Central Electrochemical Research Institute, Karaikudi 630 006, TN, India*

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Abstract

The aim of this research is to obtain electrodeposits of copper-tin over mild steel substrate. The plating parameters were studied and a model is developed using Artificial Neural Networks (ANN). The electrodeposition of copper-tin was carried out from an alkaline cyanide bath. Copper content of coatings in alloy deposition was determined by using X-ray fluorescence spectroscopy. The results were used to create a model for the plating characteristics and also for studies using ANN. The ANN model is compared with the conventional mathematical regression model for analysis.

***Keywords**:* electroplating, copper content, regression, neural network, model.

Introduction

Tremendous advancements have been achieved in the area of alloy deposition in the past two decades. This is due to the enhancement in physical properties of the deposits such as, hardness, brilliance, wear resistance, lubricity of the coatings which can not be obtained with any of the individual metals. Electrodeposition enables formation of new alloy phases, reduction in grain size, higher solubility of the solute etc., compared to the thermal methods. More over a wide range of alloy composition with varied properties could be easily obtained simply by altering parametric variables such as current density, temperature, pH, agitation and ratio of the metal ions in solution. An increase in current density, the nucleation of adatoms increases thus reducing the crystal size [1]. Generally an increase in bath temperature, increases solubility of metal ions in the electrolyte, thereby increasing the transport number and conductivity, apart from reducing the viscosity of the solution. The influence of the above enhances the operating

[*] Corresponding author. E-mail address: subbu_accet@hotmail.com

current density and hence the deposition rate. Also, higher bath operating temperature reduces hydrogen intake into the depositing metal as well as the substrate, thus reducing the tendency towards cracking due to hydrogen induced stress. Agitation of the solution reduces thickness of the diffusion layer, enabling more ions to pass through it and get nucleated. It also sweeps away the gas bubbles which cause pits. Further, to get the desired electroplating characteristics, it is essential to have a complete control over the relevant process parameters.

The objective of this study is to obtain coatings of copper-tin over mild steel substrate. The electroplating parameters were studied [2] and a mathematical model is developed for the prediction of copper content in the coatings using SPSS15 software package. The results, with particular reference to the electroplating parameters of the bath, are also predicted using artificial neural networks and compared.

K. Ramanathan et al. developed a regression model and also ANN model for the prediction of Hardness [3] and also volume percent of diamond [4] in Ni-diamond composite coatings and reported that ANN prediction is closer to experimental values than that of regression model. Numerous attempts have been reported to develop mathematical models relating process variables and bead geometry for the selection and control of the procedural variables [5-9]. Mathematical models are available for the prediction of tool life [10-15]. Models based on feed-forward neural networks in predicting accurately both surface roughness and tool flank wear in finish dry hard turning were developed by T. Özel et al. [16] and the neural network models were also compared to the mathematical regression models. It was reported that the neural network models have better prediction capabilities than regression model.

Experimental setup used for the present study

The electroplating setup used for the experiment is shown in the Fig. 1.

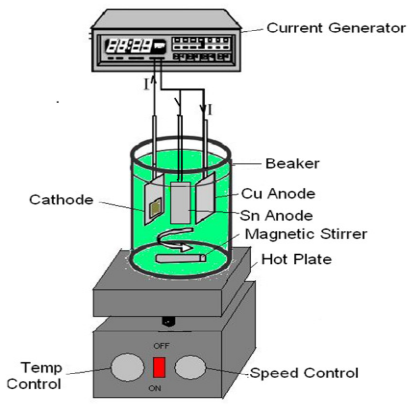

Figure 1. Electroplating setup.

The electrolyte used in this study was a cyanide system. The electroplating set up consists of two anodes (Cu and Sn anode), a cathode made of mild steel, a magnetic stirrer, current generators (rectifiers), speed and temperature control device. The distance between anode and cathode was 7 cm. The coating area was 6.25 cm^2. The composition of the bath and operating parameters for electrodeposition are CuCN-30 gpl; NaCN-45 gpl; Na_2SnO_3-42 gpl; NaOH-10 gpl; Temp-40 °C to 60 °C; pH-12.5; current density-1-5 A/dm^2. The plating parameters were optimized by varying current density from 1-5A/dm^2, stirring speed from 50-300 rpm and temperature from 40-60 ºC. A fewer number of plating experiments were carried out using electroplating setup for deposition of Cu-Sn over mild steel substrate at CECRI, Karaikudi.

The percentage of copper content in the coatings was determined by using X-ray fluorescence spectroscopy. The process variables incorporated during electroplating are current density (i), agitation speed (n) and temperature of the bath (t). The corresponding output, namely copper (Cu) content in the alloy deposition for each set of input variables was experimentally found out. The observed values of $i, n, t,$ *and* Cu are given in Table 1.

Table 1. Process variables, actual value of copper (Cu).

S.no	Process variables			Actual value
	i (A/dm^2)	n (rpm)	t (°C)	Cu (%)
1	1	50	60	81.67
2	2	50	60	74.83
3	3	50	60	72.00
4	4	50	60	70.00
5	5	50	60	69.08
6	1	80	40	84.58
7	2	80	40	79.00
8	3	80	40	78.00
9	4	80	40	76.08
10	5	80	40	74.17
11	1	300	40	89.50
12	2	300	40	85.08
13	3	300	40	84.00
14	4	300	40	81.42
15	5	300	40	78.67
16	1	300	50	86.25
17	2	300	50	84.50
18	3	300	50	83.50
19	4	300	50	80.42
20	5	300	50	75.33
21	1	300	60	83.50
22	2	300	60	75.83
23	3	300	60	73.08
24	4	300	60	70.00
25	5	300	60	71.25

Development of mathematical models

The response function representing the copper content in the alloy deposition can be expressed as $Cu = F(i, n, t)$ and the relationship selected was second degree response surface. Out of twenty five sets of experimental data available, which contain different values of process variables and the corresponding experimental outputs, twenty have been taken for training and the remaining five sets of data were taken for validation. The values of the coefficients were obtained by nonlinear regression analysis using SPSS15 software package for 95% confidence interval and convergence is achieved when the relative reduction between successive residual sums of squares is at most SSCON=1.00E-008. The value of the regression coefficients gives an idea as to what extent the control variables affect the responses quantitatively.

The less significant coefficients can be drooped along with the responses with which they are associated, without sacrificing accuracy. The significant coefficients thus selected were recalculated and final models were developed using only these coefficients. The final model thus developed for the copper content is given below:

$$Cu = a_0 + a_1 i + a_2 n + a_3 t + a_4 i^2 + a_5 t^2 + a_6 it \qquad (1)$$

The estimated values of the coefficients of the model are presented in equation 2.

$$Cu = 41.0356 - 4.0801\, i + 0.01336\, n + 2.1611\, t + 0.4088\, i^2 - 0.0241\, t^2 - 0.0231\, it \qquad (2)$$

The correlation coefficient is calculated from the formula:

$$R\ squared = 1 - \frac{residual\ sum\ of\ squares}{corrected\ sum\ of\ squares}$$

R^2-value obtained from regression mathematical model for copper content is 0.928. The validity of the equation developed is evident from the extremely high coefficient of correlation.

Validation of regression model

To test the accuracy of the model in actual applications, conformity test was conducted for the remaining five sets of data within the working limits for which different values of process variables and the corresponding experimental outputs are available. The percentages of errors, which give the deviation of predicted results of responses from the actual measured values, were also calculated and are presented in Table 2. It is found from the table that the mean absolute percentage error (MAPE) for the model is less than 2.0%.

Table 2. Comparison of actual and predicted values of copper content (Cu).

S.no	Process variables			Predicted values from SPSS	Actual values	%Error
	i (A/dm^2)	n (rpm)	t (°C)	Cu (%)	Cu (%)	Cu
1	3	50	60	71.83	72.00	0.24
2	3	80	40	78.62	78.00	-0.79
3	4	300	40	79.42	81.42	2.52
4	4	300	50	78.40	80.42	2.58
5	3	300	60	75.17	73.08	-2.78
				Mean absolute % error		1.78

$$\%\,Error = \frac{(\text{Actual Value - Predicted value})}{\text{Predicted value}} \times 100$$

MATLAB

Matlab version 7.0 is a software package used for high performance numerical computations and visualization. It provides an interactive environment with hundreds of built in functions for technical computations, graphics and animations. MATLAB stands for matrix lab. Built in functions provides excellent tools for linear algebra computation data analysis, signal processing, optimization and other scientific computations. In this work ANN module is utilized for predicting plating parameters for copper content in the alloy deposit.

Artificial neural networks

Neural networks are non-linear mapping systems that consist of simple processors, which are called neurons, linked by weighted connections. Each neuron has inputs and generates an output that can be seen as the reflection of local information that is stored in connections. The output signal of a neuron is fed to other neurons as input signals via interconnections. Since the capability of a single neuron is limited, complex functions can be realized by connecting many neurons. It is widely reported that structure of neural network, representation of data, normalization of inputs-outputs and appropriate selection of activation functions have strong influence on the effectiveness and performance of the trained neural network [17]. Methods such as Bayesian regularization, early stopping, etc., are commonly used to improve the generalization in neural networks [18]. It is advantageous to use Bayesian regularization when there is limited amount of data [19]. Number of neurons to be used in the hidden layer of a neural network is critical in order to avoid over fitting problems, which hinders the generalization capability of the neural network. Number of hidden layer neurons is usually found with trial and error approach.

A neural network usually consists of three layers i.e., input layers, hidden layers and output layer, where inputs are applied at the input layer and outputs are obtained at the output layer and learning is achieved when the associations between a specified set of input-output pairs are established.

There are different types of architecture for ANN mode. For creating a deposition model neural network requires different experimental with regard to different plating parameters and plating performance. The same twenty sets of experimental data considered for obtaining a nonlinear regression model were taken for training the artificial neural network. Normalized input data are fed to the system, which in turn gives the copper content in the deposit as output. The ANN architecture model used for the prediction of Cu has three inputs, one hidden layer and single output. In this study, copper content is predicated with a feed-forward back propagation multi-layer neural network as shown in Fig. 2.

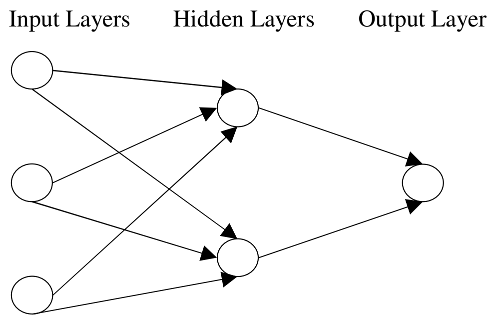

Figure 2. Structure of a neural network.

A network structure 3-2-1 is chosen for the prediction of copper content. The performance of this network is later compared with regression model. The performance curve for the prediction of copper content is shown in Fig. 3.

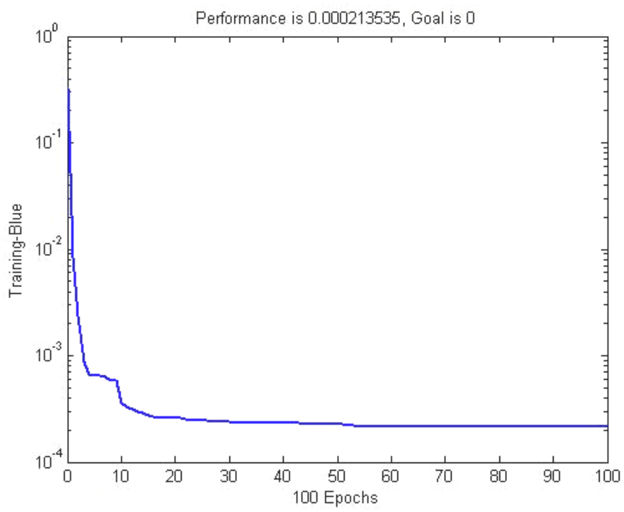

Figure 3. Performance curve for the prediction of copper content.

Validation of neural network model

To test the accuracy of the 3-2-1 neural network model for copper content, validation test was conducted for the remaining five sets of data within the working limits for which different values of process variables and the corresponding experimental outputs are available. The normalized outputs from neural network are converted to original form. The percentage of errors was calculated and presented in Table 3. It is found from the table that the mean absolute percentage error for the model is less than 1.0%.

Table 3. Comparison of actual and predicted values of copper content (Cu).

S.no	Process variables			Predicted values from ANN	Actual values	%Error
	i (A/dm^2)	n (rpm)	t (°C)	Cu (%)	Cu (%)	Cu
1	3	50	60	73.22	72.00	-1.66
2	3	80	40	77.90	78.00	0.13
3	4	300	40	81.90	81.42	-0.58
4	4	300	50	80.72	80.42	-0.37
5	3	300	60	73.72	73.08	-0.87
				Mean absolute % error		0.72

Comparison of prediction of copper content by SPSS and ANN

The copper content predicted by both SPSS and ANN is compared with the experimental values for the same five sets of validation data and the results are presented in Table 4. The comparison shows that ANN predicted model is closer to experimental than that of the mathematical regression model.

Table 4. Comparison of actual and predicted values of copper content (Cu).

S.no	Process variables			Predicted values from SPSS	Predicted values from ANN	Actual values	%Error from SPSS	%Error from ANN
	i (A/dm^2)	n (rpm)	t (°C)	Cu (%)	Cu (%)	Cu (%)	Cu	Cu
1	3	50	60	71.83	73.22	72.00	0.24	-1.66
2	3	80	40	78.62	77.90	78.00	-0.79	0.13
3	4	300	40	79.42	81.90	81.42	2.52	-0.58
4	4	300	50	78.40	80.72	80.42	2.58	-0.37
5	3	300	60	75.17	73.72	73.08	-2.78	-0.87
					Mean absolute % error		1.78	0.72

Comparison of percentage error in prediction of copper content by using mathematical regression model and the predictive neural network model is performed and shown in Fig. 4. The variation is also represented in the form of a bar chart in Fig. 5. The validation data taken for both techniques have not been used for training.

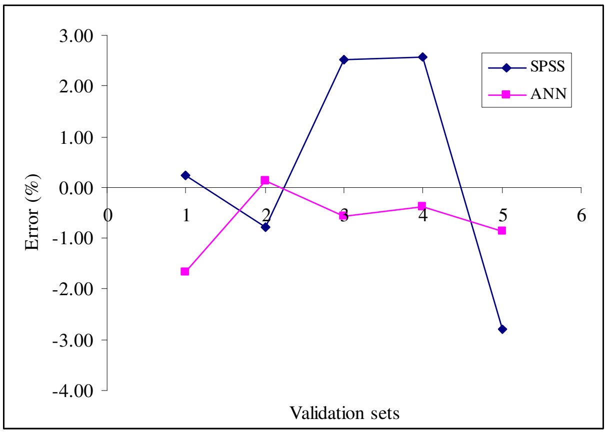

Figure 4. Comparison of percentage error in prediction of copper content using ANN vs. SPSS.

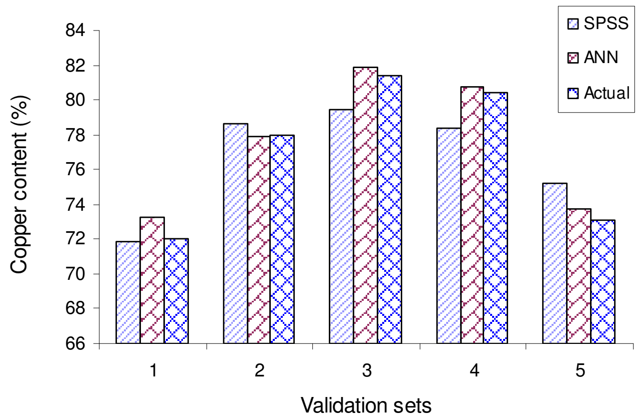

Figure 5. Comparison of actual and predicted values of copper content using ANN vs. SPSS.

Conclusion

The development of model based on feed-forward back propagation networks in predicting accurately, the copper content in the alloy deposition is carried out. The experimental data of measured copper content are utilized to train the neural network model. Trained neural network model is used in predicting copper content for various operating conditions. The developed prediction system is found to be capable of accurate copper content prediction for the range it has been trained. The neural networks model is also compared with the nonlinear regression model. The neural network model provided better prediction capabilities because they generally offer the ability to model more complex non-linearities and interactions than linear and exponential mathematical regression model can offer.

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