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Materials Letters 62 (2008) 2192–2195
materials letters
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# Neural networks prediction of different frequencies effects on corrosion resistance obtained from pulsed nanocrystalline plasma electrolytic carburizing

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Received 26 June 2007; accepted 20 November 2007
Available online 28 November 2007

**Abstract**

This paper deals with the surface modification of commercially pure titanium by using pulsed nanocrystalline plasma electrolytic carburizing. In order to fully characterize the complex underlying mechanism of this process and evaluate the effects of a thorough range of frequencies, a prediction model is developed using a hybrid of Neural Networks and Genetic Algorithms (GA). Process variables, i.e. time, frequency and corrosion resistance of nanocrystalline carbides, have been experimentally studied. Corrosion resistances were measured by PDS technique for different coated samples. A portion of this dataset is used to train the prediction model, while the rest is set aside to test its predictive performance. This hybrid Neural Networks model uses GA to achieve its optimal architecture for prediction. Finally, it is concluded that the proposed model has an excellent prediction capability of final corrosion resistance of nanocrystalline carbides in the various range of frequencies by comparing the results with the experimental data.


*Keywords:* Corrosion resistance; Genetic algorithm; Model; Neural network; Pulsed nanocrystalline plasma electrolytic carburizing

## 1. Introduction

### 1.1. Problem context

This work was aimed at providing a better understanding of the estimation of the growth of nanocrystalline carbides in the wide range of frequencies during the formation of them on commercially pure titanium (CP-Ti) under pulsed cathodic nanocrystalline plasma electrolysis [1–6] in glycerol based electrolyte. The objective was to complete two earlier works; first the influence of pulsed nanocrystalline plasma electrolysis on the kinetics and morphology of performed nanocrystals [7], the other one for providing a better understanding of the relation between the different parameters during the formation of nanocrystals on substrate under nanocrystalline plasma electrolysis [8]. At a given applied voltage, the frequency was the parameter that governed the nature of the nanocrystallized phases that formed, by controlling the applied voltage due to duty cycle of pulsed current, titanium carbides was obtained for different frequencies.

## 2. Experimental procedure

Carburizing was performed in Glycerol based electrolyte similar to our other previous works [9,10]. The surface and cross-section morphologies and chemical composition of PNPEC films were examined by XL-30 (PHILIPS) scanning electron microscope. The working electrodes were CP-Ti with 10 $cm^2$ area. Sample surfaces were polished with silicon carbide (particle size 25 μm), rinsed thoroughly with acetone and carefully dried. Corrosion tests with the use of potentiodynamic polarization and Stern–Geary equation were performed to determine corrosion resistance of treated samples. Corrosion tests were done by a potentiostat/galvanostat (EG&G 273A, Princeton Applied Research), a standard

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doi:10.1016/j.matlet.2007.11.052

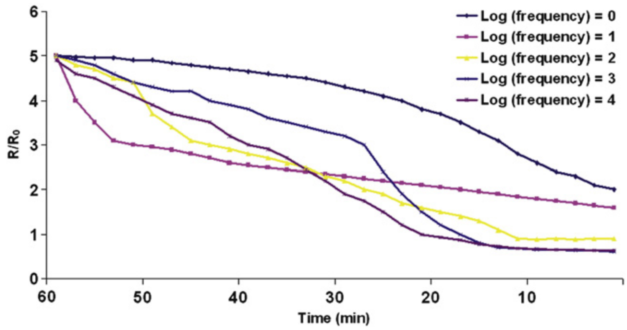


Fig. 1. Experimental data at different frequencies.

cell and electrode holders. SCE was used as the reference electrode and the counter electrode consisted of platinum plate. The surface area exposed to the electrolyte was 0.785 $cm^2$. The pulser box generated a rectangular pulsed potential signal to the specimen surface. This arrangement allowed both the period and frequency of the signal to be set independently of each other. The applied potential signal profile was monitored on a digital oscilloscope. Experiments were driven under constant current conditions using a current regulator box. This box remained the average amount of pulsed current to maintain a constant level. Duty cycle of pulsed current was 40% for all of the tests. Fig. 1 illustrates the experimental data as a result of constant current technique at different frequencies. Here $R_0$ represent the corrosion resistance of raw substrate.

## 3. Proposed neural network model

The proposed model is as follows. We divide 229 available observations to three subsets, a training set containing 50% of the data (113 random observations), a validation set containing 25% of the data (58 random observations) and a testing set containing 25% of the data (58 observations). The training dataset will be used to train the neural networks in each generation of GA and the validation set will be used to evaluate the goodness of these networks and choose which ones to survive to the next generation. The test dataset will be used to evaluate the performance of the best network chosen at the end of the GA generations.

The first step is to create an initial population of 50 chromosomes (network architectures) randomly and train them on the training set and evaluate them on the validation set to find their fitness. After that, the parent chromosomes are selected according the roulette wheel selection scheme. These parents will be used to generate the next population. The next step is to cross-over the parents with a probability of 0.9 and mutate them with a probability of 0.01. The single-point cross-over and the uniform mutation are used.

After generation of the new population, all of the chromosomes of this newly created population will undergo a training process to find their fitness value. This process is repeated iteratively until the algorithm converges (no improvement in the fitness value of the best member of the successive populations) or a maximum number of generations (100 in this study) is reached.

By completion of the GA process, the best member of the last generation would be the optimal neural network architecture. This architecture is then trained using all of the training and validation data and then tested on the testing dataset to measure the generalization of the achieved neural network.

## 4. Result and discussion

The model proposed in previous section was implemented in Matlab 7.0 environment. The best neural network architecture shown by the GA procedure is a [2 10 2] neural network with tangent hyperbolic activation function for all of the layers.

The performance criteria on the train, validation and test datasets are reported in Table 1. Prediction error on the test dataset is shown in Fig. 2.

For further validation of the results, we also decided to test this network in some new frequencies which have not been seen by the network. The predictions of the neural network for these frequencies are quite reasonable.

The microstructure of the layer is dependent on crystallization and growth. After a strong pulse, when the electrolyte in the vicinity of the electrode is depleted in cations, material supply occurs in the 'off' time during which adsorption and desorption phenomena can occur. The 'off' time also allows the rapid quench in electrolyte that can affect the coating process. On the other hand, the diffusion of several species, originating from the electrolyte, determines the surface diffusion of the new atoms, which affects their incorporation to new nanocrystallites. These result in a change in the structure and also porosity of compound layer which are influenced by pulse parameters.

Fig. 3 shows the predicted $R/R_0$ values after 10, 15, 20, 30 and 60 min of coating times by applying pulsed voltage. The temperature of electrolyte, duty cycle, Glycerol concentration and applied voltage were set to 30 °C, 40%, 1100 g/l and 600 V respectively. The simulated results show that the minimum final corrosion resistance was obtained at moderate frequencies. As shown in this figure, increasing the frequency generally increases the corrosion resistance. In contrast, the minimum $R/R_0$ values have been observed at frequencies between 350 and 450 Hz. Such inversions of the role played by a given parameter might be due to the change of ion diffusion time on the interface between a cathode and solution caused by changing the frequency which varies the 'On' and 'Off' time. At very high frequencies, quenching of compound layer at the electrode surface cannot occur, and the process run at a low average current, so it could be the reason for higher final corrosion resistance and lower deposits growth rate at more than 1000 Hz frequencies.

Table 1
Performance criteria for train, validation and test datasets

| Performance criteria | Train | Validation | Test |
|---|---|---|---|
| MSE | 0.00026 | 6.606e−5 | 0.00026 |
| RMSE | 0.0161 | 0.0081 | 0.0161 |
| MAE | 0.00962 | 0.00526 | 0.00962 |
| Max AE | 0.0714 | 0.0361 | 0.0714 |
| MAPE | 0.0358 | 0.0285 | 0.0358 |
| Max APE | 0.1546 | 0.241 | 0.1546 |
| $R$-square | 0.997 | 0.999 | 0.997 |

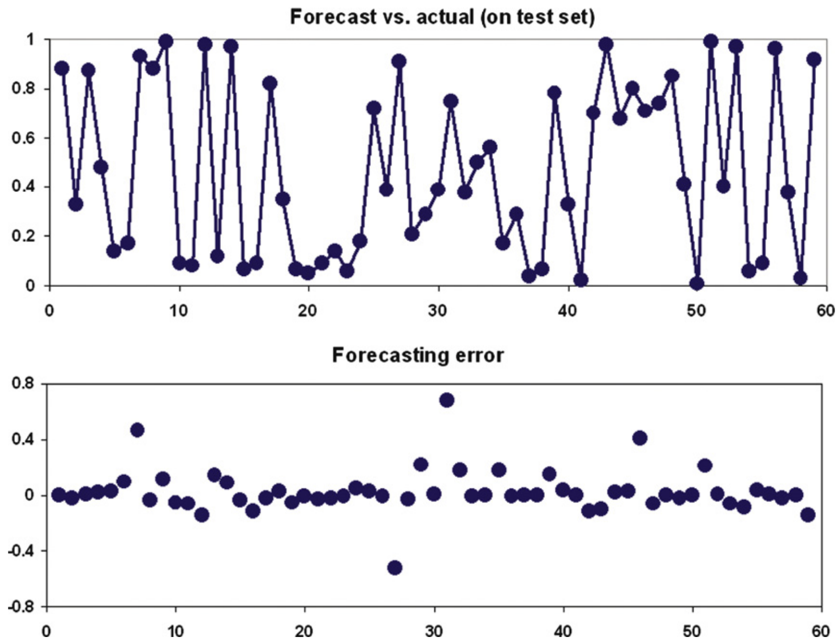


Fig. 2. Prediction error on test dataset.

It is generally agreed that the diffusion rate in the pulsed technique is governed by the pulsed current and other parameters such as 'on' time and 'off' time. At a given peak current, the amount of the last two parameters determines the kinetics and morphology of the formed layer. The use of pulsed current caused the intense decrease in surface potential toward adsorbing accelerated radicals and this facilitates formation of the compound layer, and also decreases the kinetics of layer formation compared with continuous current.

Finally all the achieved results were related to the size of the nanocrystalline carbides and it has been revealed that by the optimum levels of effective factors on PNPEC process, the higher corrosion resistances will achieve by lower sizes of nanocrystalline carbides. Fig. 4 shows these results and is an evidence for this conclusion.

## 5. Conclusions

A new hybrid technique using neural networks and GA has been utilized to study scale deposition on metal surface. This model has provided evidence for the influence of wide range of frequencies on the kinetics and morphology of compound layer formation.

The model shows a complicated effect of frequency. It is concluded that the best surface coverage was obtained at frequencies more than 300 Hz. But at very high frequencies, the kinetics of layer formation was relatively deducted. However, the maximum kinetic of layer formation by pulsed current and minimum corrosion resistance were deduced at 400 Hz of frequency. Finally, the neural network solutions were found to be a very promising technique for modeling the experimental data as the latter is strongly affected by non-linearity, and consequently is not suited to the application of regression models. There are some limitations in industrial usage as they must be considered for designing these units, as the edge effect for uniform sparking around the sample and electrolyte agitation around the sample. The maximum and minimum corrosion resistance that achieved by this method is about 600 and 60 MΩ for coated samples.

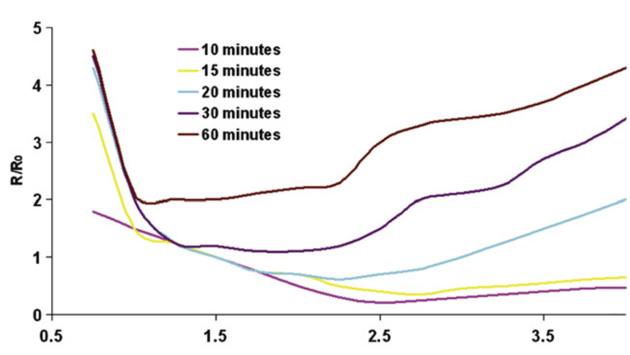


Fig. 3. Predicted value for unseen frequencies.

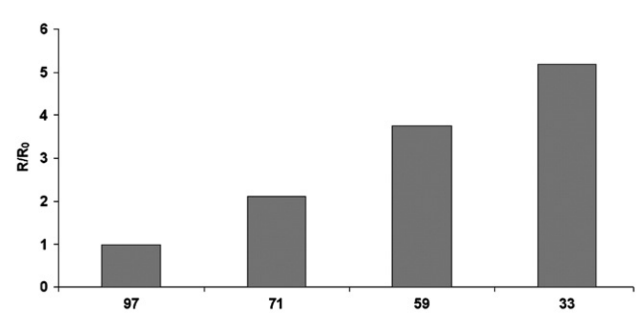


Fig. 4. Relation between the size of nanocrystalline carbides and corrosion resistance improvement.

## Acknowledgements

The authors would like to express their thanks to national association of nanoscience and nanotechnology of Iran and Arvandan Oil and Gas Company (TMU 85-09-66) for financial support of this project.

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