Available online at www.sciencedirect.com
SCIENCE DIRECT®
Corrosion Science 47 (2005) 1625–1642
CORROSION SCIENCE
www.elsevier.com/locate/corsci

Neural network analysis for corrosion of steel in concrete

Thirumalai Parthiban *, R. Ravi, G.T. Parthiban, S. Srinivasan, K.R. Ramakrishnan, M. Raghavan

Central Electrochemical Research Institute, Karaikudi 630 006, India

Received 15 August 2003; accepted 24 August 2004

Abstract

Corrosion of the steel embedded in concrete plays a vital role in the determination of life and durability of the concrete structures. Several researchers have studied the corrosion behaviour of the embedded steel and the different types of protective measures that are available to control the corrosion. However, little work has been done to recognize, identify the performance and predict the behaviour of the steel over a long term. Hence, this work concentrates on recognizing the behavioural pattern of the embedded steel and predicting its potential characteristics using artificial neural network (since the potential of the embedded steel is used to determine whether the steel is corroding or not as per ASTM C 876-91).

A systematic study to develop a suitable method that can accept, analyze and evaluate experimental data that are at random and/or influenced by external, unpredictable variables has been carried out, using the back propagation method. This method is fast and is able to produce an output that has minimum error for this experimental setup. This has resulted in the development of back propagation neural network, that can train and test the system, to calculate the specified parameter for different conditions and recognize the behavioural pattern. Using this methodology, the corrosion of the steel embedded in concrete is analyzed and it is observed that the error encountered is only about 5% for the predictions made from the analysis.

* Corresponding author.
E-mail addresses: thirumalaip@yahoo.com (T. Parthiban), yegna1234@hotmail.com (R. Ravi).

0010-938X/$ - see front matter
doi:10.1016/j.corsci.2004.08.011

Keywords: Steel; Neural network analysis; Concrete corrosion

1. Introduction

Steel reinforcement corrosion is a very expensive problem since it leads to unanticipated, premature degradation of concrete structures and buildings. In most cases, water-soluble chlorides induce the corrosion of the reinforcement steel. The reactions probably occur continuously in concrete in the presence of chloride. As the corrosion of the embedded steel continues, the products formed exert enormous stress on the surrounding concrete leading to cracking and later spalling of the concrete. These stresses have been reported be as high as 450 MPa [1].

Corrosion of steel in concrete is retarded by the passivating ferric oxide film (γ-FeOOH) formed in the concrete medium (which is highly alkaline with a pH around 12.5). However, this passive film is broken and corrosion is facilitated in the presence of chloride when the ratio between the chloride and hydroxide in concrete exceeds 0.6 [2]. Many studies for modeling the corrosion of steel and its effects in concrete have been carried out [3–15]. These models have been developed for specific conditions with assumptions such as uniform oxygen concentration distribution, rapid formation of the hydroxide film on steel etc. These models have been reported to agree with the qualitative expectations of the corrosion behavior in the system. The extent of agreement has been observed to vary depending on the aggressiveness of the system. However, long term predictions using any of these models has not been reported. Hence, a quantitative analytical system is necessary to be developed to predict and analyze the behavior of the steel in concrete. In most cases, the corrosion of the embedded steel is monitored by measuring the potential of the steel. The potential is compared with those reported in international standards [16–18] and the condition of the steel is deduced.

Artificial Neural Networks (ANNs) are computational systems whose architecture and operation are inspired from our knowledge about biological neural cells (neurons) in the brain. ANNs can be considered as collections of very simple "computational units" which can take a numerical input and transform it, usually via summation, into an output [19–25]. ANNs can be described either as mathematical and computational models for non-linear function approximation, data classification, clustering and non-parametric regression or, as simulation of the behavior of collection of model biological neurons. ANNs can be used in a variety of powerful ways: to learn and reproduce rules or operations from given examples; to analyze and generalize from sample facts and make predictions from these; or to memorize characteristics and features of given data and to match or make associations from new data to the old data. Neural network analysis serves as a highly useful tool for analyzing and predicting the behavior of systems that cannot be described by any analytical equations. One of the distinct characteristics of the artificial neural network (ANN) is its ability to learn from experience and examples and then to adapt with changing situations.

Hence, this neural network approach has been adopted to analyze, interpret and predict the potential of the embedded steel in concrete slabs under two different conditions viz. without chloride (less probability for corrosion) and with chloride (high probability for corrosion). These measurements were done in a lab level system and the potential was measured at specified durations.

2. Experimental

For the present study, concrete slabs of size 1 m × 1 m × 0.1 m under investigation in the laboratory were used. These test slabs were cast with steel embedded in it with a cover thickness of 0.02 m. All these slabs were left in open atmosphere.

Following are the conditions of slabs on which measurements were taken:

(a) Slab 1: without chloride and
(b) Slab 2: with chloride (3.5% NaCl added by weight of cement).

The potential of the steel was measured at different locations on each slab, using a data acquisition system (NI-DAQ card AT-MIO-16E-10). The principle involved in this method is appearance of an electrical potential between the reinforcing steel and a reference electrode (copper–copper sulphate electrode). The reference electrode was moved across the concrete surface to be investigated, and the electrode potentials were measured at different locations. In all, the potential of the embedded steel rods were acquired at 36 different marked locations in each slab periodically. The data acquired were stored in a data file. For each slab, the data acquired was averaged and this was used for analysis by the neural network software.

The measured and predicted potential values were compared to ASTM standard C876-91, and interpreted correspondingly.

ASTM standard C876-91	
Potential level (V)	Probability for corrosion
<−0.350	>90%
−0.200 to −0.350	50%
>−0.200	90% no corrosion

Software modules were developed using Visual Basic, MS Access and MS EXCEL. Back propagation neural network (BPN) was used for analyzing the behavior of the concrete slabs under investigation. Back propagation network was trained and optimized for predicting the behavior of the system under investigation.

For each slab, data were split into two data sets one of which was a training set and the other was the test set. The selection of an adequate number of training patterns is therefore, an extremely important issue. There are no acceptable generalized rules to determine the size of the training data for suitable training. Data chosen for training must cover upper and lower boundaries of the data set. Sufficient number of samples representing particular features over the entire training domain is necessary. A well trained network is one which is able to respond to any unseen pattern within an appropriate domain. The neural net uses the training set with the time intervals being the input data and the potential being the output data for the concrete slabs. The training set is used to adjust the network weights and to determine when to terminate the training. The reduction in error below a threshold value, between the potential data calculated by the neural network and actually measured potential data is used as the criterion to stop the training. The test data set is used to assess the performance of the BPN by presenting the data that do not form part of the training set. In this, different sets of training and test data were chosen from the entire range of data.

2.1. Preprocessing of data

Neural networks have been shown to be able to process data from a wide variety of sources. They are however, only able to process the data in a certain format. Furthermore, the way the data is presented to the network affects the learning of the network. Therefore, a certain amount of data processing is required before presenting the training patterns to the network. For better and smoother network generalization, it may sometimes be necessary to remove some of the data outliers. Removing data outside these ranges will greatly improve network training, provided that these data are extreme and uncharacteristic of the problem domain. Data scaling is another essential step for network training. One of the reasons for preprocessing the output data is that a sigmoidal transfer function is usually used within the network. Upper and lower limits of output from a sigmoid transfer function are generally 1 and 0 respectively. It is therefore recommended to normalise the input and output data before presenting them to the network. Scaling of the data has been done individually, i.e. over their own range rather than over the whole range for all the inputs. This preprocessing of the data has been done to scale all the data in the 0 to 1 range. The input and output nodes are next normalized between 0 and +1. The network generalization is improved if the output layer is scaled to exploit less than the full range of the normalized scale, and the optimum for output variable appears typically to be between 0.1 and 0.9. Separate module has been developed in the software for preprocessing the data.

Back propagation neural network: Before training commences, the connection weights to the hidden and output layers are set to small random values. The network was trained for a range of cycles. Learning rate and the momentum values were also varied in the range 0.01–1 and 0–1 respectively. Here the number of cycles was varied up to a specified range. Separate routines were developed in the software for initializing the weight values, setting the range of values for different parameters like momentum (alpha), learning rate (beta) and storing the optimum values selected for the network to generalize for unknown data. The neural net used the training set with time intervals being the input data and the potential being the output data. The input pattern is applied to the network, which is allowed to run until an output is produced at each output node. The differences between the actual output and that expected, taken over the entire set of patterns, are fed back through the network in the reverse direction to signal flow modifying the weights as they go. This process is repeated until a suitable level of error is achieved. For any given ANN, set of connection weight values, and training set there exists an overall root mean squared (RMS) error of prediction. One complete calculation involving all the training patterns is called an epoch. This is equivalent to one complete pass through all the training data, calculating and summing the errors between the desired and calculated output for each member of the training set. In the back-propagation algorithm used here, the weights are updated after all the training data are seen.

In order to determine the optimal number of hidden layer nodes, neural networks with different number of hidden layer nodes were trained, for the slabs under investigation. For the experimental data used to train the network, the optimum number of hidden layer nodes was chosen when the error was minimum, by varying the learning rate and momentum. It was found that when the momentum was equal to some optimum value, the network could achieve faster convergence and avoid getting trapped in a local minimum, while lower momentum would not allow the network to attain a minimum error. With higher momentum, the error on prediction soon started to oscillate without settling to a minimum. So the momentum was set to an optimum value. Using these optimum values for learning rate, momentum, training cycles and number of nodes in the hidden layer, the network was tested for the unknown data (data not presented to the network during training). In this, different sets of training and test data were chosen from the entire range of data. Separate modules have been developed in the software for data scaling and preprocessing.

Stability and convergence: During training, root mean square error was calculated for number of epochs to estimate the extent of training. Training may be said to have finished when the network has found the lowest RMS error, provided the network has not become stuck in a local minimum and this point is referred to as the global minimum on the error surface [25]. The error between the output seen and that expected has been calculated for the test set. Training has been, stopped when the RMS error on the test or cross-validation data is lowest. Once trained to the best generalization point, the neural network may then be challenged with unknown data, which have not seen by the network.

The results obtained from the neural network were compared with the experimental values and the pattern of behavior of the system was determined. Measuring at random reconfirmed the validity of the recognized pattern.

3. Results and discussion

The analysis and prediction of the potential of the steel was carried out with different sets of training and testing data. The network was generalized with an input layer, one hidden layer (number of neurodes vary for each set of data) and an output layer. The results of the analysis for each set of data and the corresponding predictions are discussed below.

3.1. Slab 1

At the initial stages, where the variations were considerably large, a set of data up to 3334 h was chosen for analysis. From this set, data was selected randomly for training and testing [26–30]. Nearly 75% among the data were used for training while the remaining 25% were used for testing. The test data selected were in the lower range for the prediction and extrapolation up to 8000 h. The data from the training set was used to determine the number of neurodes in the hidden layer, which resulted in the least error between the neural network output and the experimental data. The hidden layer neurode number was varied and the resulting root mean square (RMS) errors between the network outputs and the corresponding experimental outputs were determined. The number of neurodes evaluated ranged from 1 to 30. From this, the number of neurodes with their corresponding minimum error was selected and plotted. This is illustrated in Fig. 1. It can be seen from the figure that the error is minimum when the number of neurodes is 8.

The next step involved the identification of the number of cycles (training periods) for these 8 neurodes, for the minimum error to be got. The number of cycles tested ranged from 100 to 1000. However, the range of cycles exhibiting minimum error was observed to be in the range 140–200. This range of cycles with minimum error is plotted against the corresponding error for each cycle as illustrated in Fig. 2. As the number of cycles increases, the error decreases up to about 160 cycles. Beyond this, the error increases. From this figure, it can be seen that the error is the lowest when the number of cycles is 160. Hence, 8 neurodes in the hidden layer were chosen as the architecture for the neural network used in this analysis. The maximum error encountered by this architecture is only about 5.37%, as illustrated in the figure. Using this architecture, with the optimized adjustable parameters, the behavior of the system under consideration is generalized.

The generalized behavior obtained for this test system is illustrated in Fig. 3. In this figure, the neural network outputs for the training data inputs are seen to be clo-

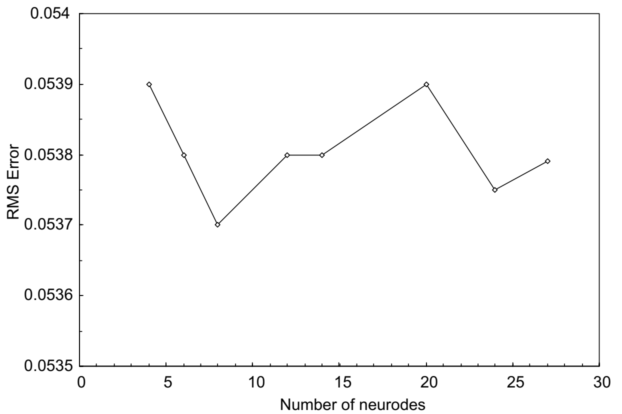

Fig. 1. Error generated by different number of neurodes in slab 1.

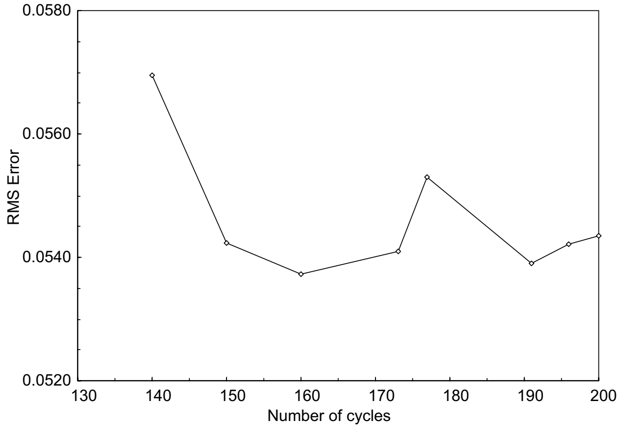

Fig. 2. Error generated by different number of cycles in slab 1.

sely distributed about the experimental curve. The neural network developed is able to closely follow the experimental curve. The validity of the test data set is also tested and can be seen to match the results obtained for the training data set. The neural network outputs (predicted potentials) for both the training and test data are observed to fit well with the experimental data. This is also illustrated in Fig. 4 where the predicted values for different times of measurement are plotted against the experimentally measured values for the corresponding times of measurement (acquired data). The fit is observed to be linear with a slope of 0.77. These observations are in good agreement with similar investigations using neural network [31,32].

As the next step, the network was evaluated for different time intervals of measurement, which were not used in the training set. These timings were chosen in a manner such that they are beyond those assigned for the training set, similar to

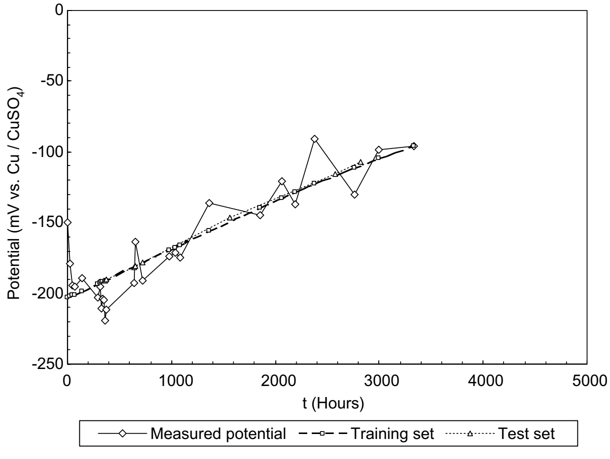

Fig. 3. Validation of test data set with the training data set and experimental values for slab 1.

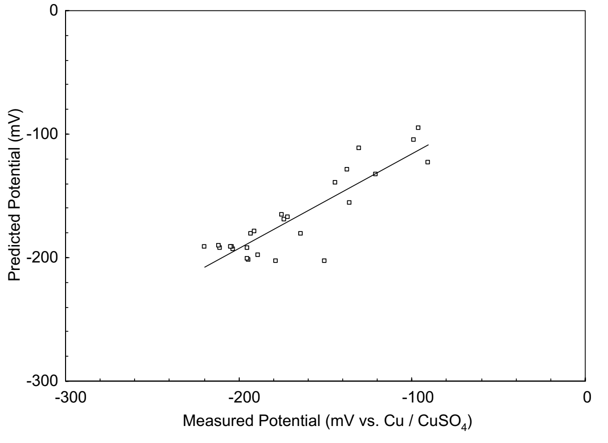

Fig. 4. Correlation between the predicted potentials and the experimentally measured potentials for slab 1.

extrapolation. This was carried out in order to verify the different claims made [29,31]. The values of the potentials estimated from the neural network outputs are plotted along with the experimentally measured potentials in Fig. 5. It is observed that these calculated/predicted potentials vary from 5 to 25 mV only, from the experimentally measured potentials, up to a maximum of 8000 h. The variation is observed to be more as the time intervals for which prediction is made by the network are shifted farther away from the time intervals used for evaluating network outputs with the training set.

Then calculation of network outputs for a longer time range with the same data, from a different training set was also studied. Here the data for the training set and

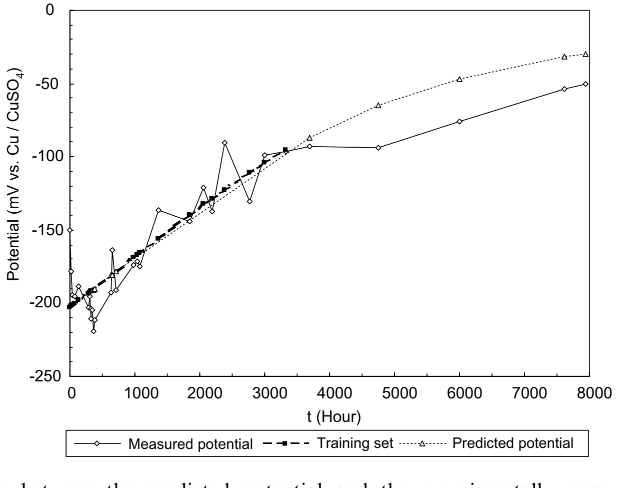

Fig. 5. Correlation between the predicted potential and the experimentally measured potential, on extrapolation, for slab 1.

test set were populated over the time range of 3334 h, since the extrapolation range had to be widened [33]. The number of neurodes in the hidden layer was determined for calculating the potential values up to 15,000 h as the first step and the RMS error was evaluated determined for different number of neurodes. It was observed that the error is the lowest, when the number of neurodes is 5.

Similarly, the next step involved the identification of the number of cycles (training periods) for these 5 neurodes, with minimum error. The number of cycles tested ranged from 100 to 1000 and the RMS error encountered by the different number of cycles were calculated. The range of cycles exhibiting minimum error was observed to be between 500 and 600. As the number of cycles increases from 500, the error decreases up to about 516 cycles. Beyond this, the error increases marginally up to about 580 cycles and then increases rapidly. Beyond 600 cycles, the error again decreases. But this decreased error is still higher than that for 516 cycles. Hence, 5 neurodes for 516 cycles were chosen as the architecture for this neural network analysis (extrapolation to 16,000 h). Using this architecture, with the optimized adjustable parameters, the behavior of the system under consideration was again generalized and the slope was calculated from the plot for predicted values versus experimentally measured values. The slope of the line is observed to be 0.79, indicating that the fit has a higher degree of accuracy.

The accuracy of prediction by the optimal network over a longer time interval range was also evaluated, by using a new training set. Here the data for the training set and test set were populated over the range of data up to 10,000 h, to facilitate the lengthening of the range of the network validity. The number of neurodes in the hidden layer was determined for evaluating the test data up to 20,000 h. RMS error determined for the different number of neurodes in the hidden layer is the lowest, when the number of neurodes is about 4.

The number of cycles (training periods) for these 4 neurodes, with minimum error was then evaluated. The number of cycles tested ranged from 100 to 1000. The range of cycles exhibiting minimum error was calculated and observed that the error is minimum between 150 and 200. As the number of cycles increases from 150, the error decreases up to about 166 cycles. Beyond this, the error increases marginally up to about 200 cycles. Hence, 4 neurodes for 166 cycles were chosen as the architecture for this neural network analysis (extrapolation to 20,000 h). Using this architecture, with the optimized adjustable parameters, the behavior of the system under consideration is again generalized.

The validity of the test data set is also tested with this network realized using the training data set. Here again, it is observed that network output for test data fit very well with the observed experimental values. The predicted values (network output when test data set is used as input to the network) for different times of measurement were plotted against the experimentally measured values for the corresponding times of measurement (acquired data) and are shown in Fig. 6. The slope of the line is observed to be 0.94, indicating that the fit has a very high degree of accuracy.

The network was again evaluated for different times of measurement, which were not used in the training set. These timings were again chosen in a manner such that they are beyond those assigned for the training set. This was again carried out in

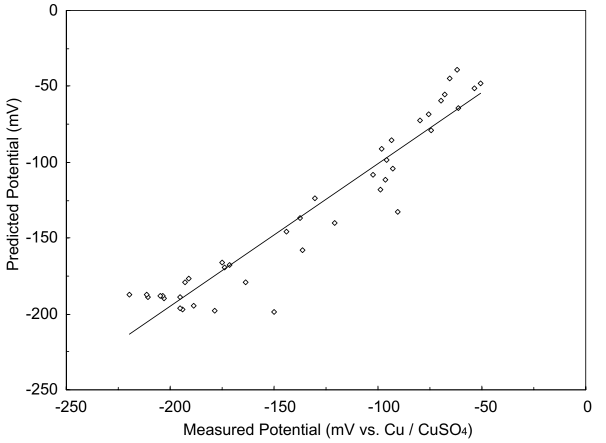

Fig. 6. Correlation between the predicted potentials and the experimentally measured potentials, based on larger training set, for slab 1.

order to check the validity of the predictions (outputs from the network developed with the training set) at much longer times for this network. The values of the potentials estimated from the network were compared with the experimentally measured potentials. It is observed that these calculated/predicted potentials vary by 0–30 mV only, from the experimentally measured potentials, up to a maximum of 20,000 h. Here, the variation is observed to be very low near the training set as well as farther from it, as compared with the patterns obtained using the training set up to 3334 h.

For this particular test system (slab 1), the entire range of measured data, up to nearly 28,600 h, was taken for recognizing the pattern and extrapolation. The accuracy of prediction from the network developed with data over a longer range, from a new training set, was then studied. The number of neurodes in the hidden layer was determined for predictions up to 35,000 h. RMS error determined for the different number of neurodes were evaluated and it was observed that when the number of neurodes equals 2, the error is the lowest. It was also observed that the RMS error increases as the number of neurodes increases further.

Next, the number of cycles (training periods) for these 2 neurodes, with minimum error was identified and it was seen that the RMS error is the least when the number of cycles was about 160. As the number of cycles increases beyond 160, the error increases. Hence, 2 neurodes for 160 cycles were chosen as the architecture for this neural network analysis (extrapolation to 35,000 h). Using this architecture, with the optimized adjustable parameters, the behavior of the network under consideration is again generalized.

The network was again evaluated for different times of measurement, which were not used in the training set. These timings were again chosen in a manner such that they are beyond those assigned for the training set. This was again carried out in order to check the validity of the network for predictions at much longer times for the present training set. The variation is observed to be very low near the training set as well as farther from it, as compared with the patterns obtained using the training sets earlier. The predicted values for different times of measurement were plotted against the experimentally measured values for the corresponding times of measurement (acquired data), and the slope of the line was observed to be 0.943, indicating that the fit has a very high degree of accuracy.

Fig. 7 compares the predictions made by the neural network with the data for training from two different sets. One set of training data was taken from the measured data up to 10,000 h and the other set of training data was taken from the measured data up to 28,600 h. From the figure it can be clearly seen that the training data chosen from 28,600 h yields a more reliable network architecture than the other set.

3.2. Slab 2

BPN software developed was used to analyze the data acquired for slab 2 also.

At the initial stages, where the variations were considerably large, a set of data up to 3334 h was chosen for analysis. From this set, data was selected randomly for training and testing, similar to slab 1. Nearly 75% among the data were used for training while the remaining 25% were used for testing. The test data selected were in the lower range for the prediction and extrapolation up to 8000 h. The data from the training set was used to determine the number of neurodes in the hidden layer. Different number of neurodes in the hidden layer was evaluated and the resulting RMS errors were determined. The number of neurodes evaluated ranged from 1 to 40 and their corresponding errors were plotted in Fig. 8. It can be seen from the figure that the error is minimum when the number of neurodes is 16. The next step involved, the identification of the number of cycles (training periods) for these

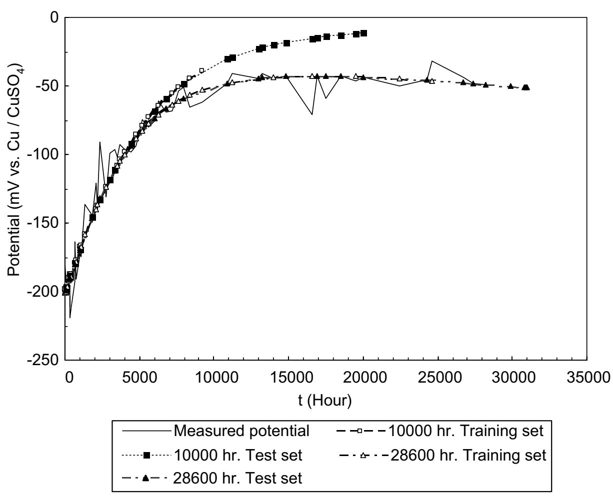

Fig. 7. Comparison of the predictions made with the data for 10,000 and 28,600 h for slab 1.

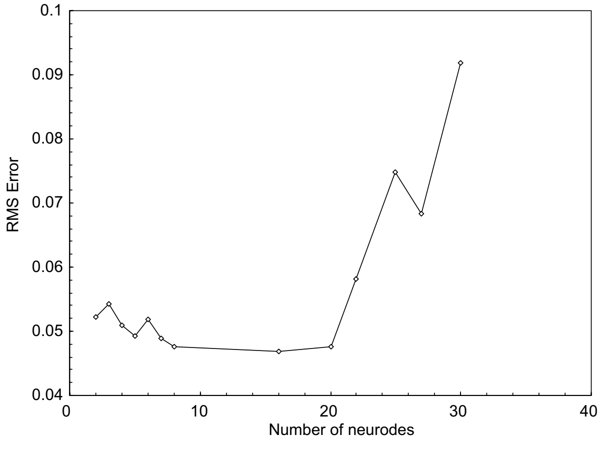

Fig. 8. Error generated by different number of neurodes in slab 2.

16 neurodes, with minimum error. The number of cycles tested ranged from 1 to 200. However, the number of cycles exhibiting minimum error was observed to be between 100 and 200. This range of cycles was plotted against the corresponding error for each cycle and is illustrated in Fig. 9. As the number of cycles increases from 100, the error decreases up to about 140 cycles. Beyond this, the error increases gradually. From this figure, it can be seen that the error is the lowest when the number of cycles is 142. Hence, 16 neurodes for 142 cycles were chosen as the architecture for neural network analysis. The maximum error encountered by this architecture is only about 4.7%, as illustrated in the figure. Using this architecture, with the optimized adjust-

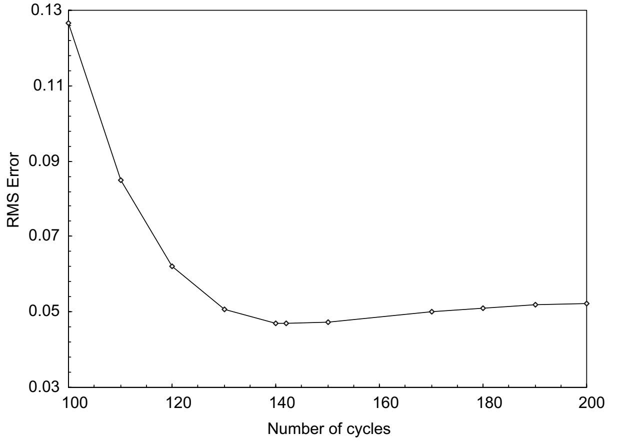

Fig. 9. Error generated by different number of cycles in slab 2.

able weight parameters and 16 neurodes in the hidden layer, the behavior of the network under consideration (for slab 2) is generalized.

The generalized behavior obtained for this network with test data is illustrated in Fig. 10. In this figure, the network developed using the training data is again observed to result in a network with outputs showing minimum errors for test data, similar to slab 1. The validity of the network when tested with test data set has minimum errors between network outputs and the experimental data. It is also observed to fit well with the network. This is also illustrated in Fig. 11, where the predicted values for different times of measurement were plotted against the experimentally measured values for the corresponding times of measurement (acquired data). The fit is observed to be linear with a slope of 0.699. This fitting is having a relatively lesser proximity for the slope value equal to 1 (which will be the best fit), indicating that the accuracy of the fit is relatively less. This may probably be due to the large variations in potential observed at the initial stages.

As the next step, the network was evaluated for different times of measurement, which were not used in the training set. These timings were chosen in a manner such that they are beyond those assigned for the training set, similar to extrapolation. The values of the potentials estimated from the pattern are plotted along with the experimentally measured potentials in Fig. 12. It was observed that these calculated/predicted potentials vary widely from the experimentally measured potentials, up to a maximum of 8000 h, as the time interval for prediction is selected farther and farther from the training data.

The accuracy of prediction from the network with data over a longer range, from a new training set was then studied. Here the data for the training set and test set were populated over the range of data up to 10,000 h, to facilitate the lengthening of the predicted range and to increase the accuracy. The number of neurodes in

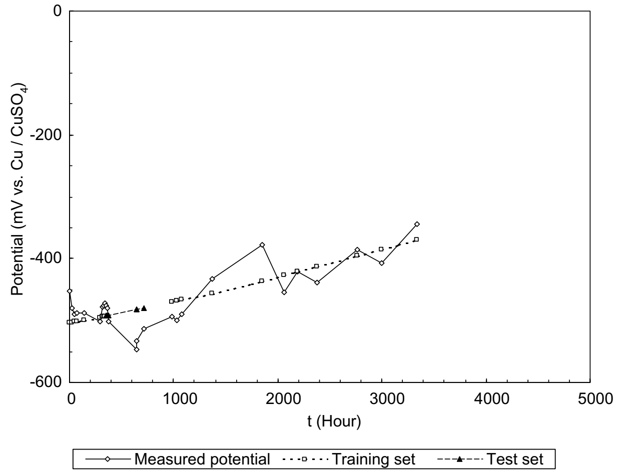

Fig. 10. Validation of test data set with the training data set and experimental values for slab 2.

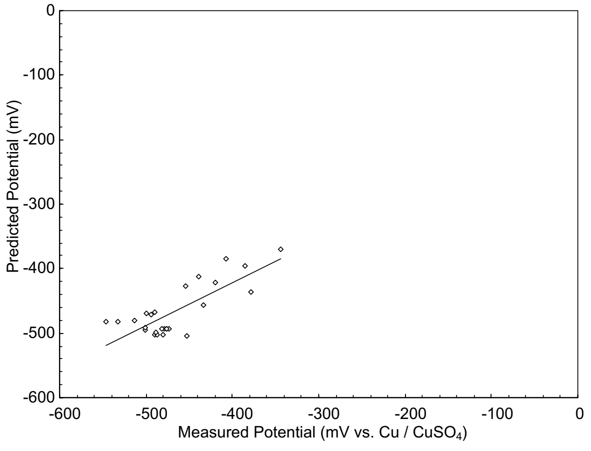

Fig. 11. Correlation between the predicted potentials and the experimentally measured potentials for slab 2.

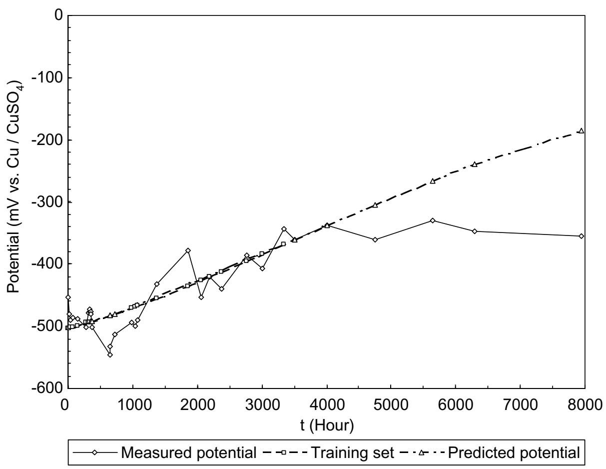

Fig. 12. Correlation between the predicted potential and the experimentally measured potential, on extrapolation, for slab 2.

the hidden layer was determined for predicting outputs for time intervals up to 20,000 h. The RMS error was evaluated for different number of neurodes and it was observed that the error is the lowest, when the number of neurodes equal to 2. It was also observed that the RMS error considerably decreases as the training domain is widened.

The number of cycles (training periods) for a hidden layer with 2 neurodes, with minimum error network outputs was then identified it was evaluated as 139 cycles for this neural network analysis (extrapolation to 20,000 h). Using this architecture, with the optimized adjustable parameters, the behavior of the system under consideration was again generalized.

The generalized behavior obtained for the test system is illustrated in Fig. 13. In this figure, the network showing outputs for test data inputs and the experimental data tend to agree with reasonable error. The validity of the test data set was also tested with the network realized with the training data set. Here again, it is observed that the network outputs fit very well with the experimental outputs. The predicted values for different times of measurement were plotted against the experimentally measured values for the corresponding times of measurement (acquired data) and are shown in Fig. 14. The slope of the line is observed to be 0.83, indicating that the fit has a considerable degree of accuracy.

For this particular test system (slab 2), the entire range of measured data, up to nearly 28,600 h, was taken for recognizing the pattern and extrapolation. The accuracy of prediction from the network with data over a longer range, from a different training set, was then studied. The number of neurodes in the hidden layer was determined for recognizing the pattern up to 35,000 h. The RMS error was evaluated for different number of neurodes. It was evaluated that when the number of neurodes was 4, the error was the least.

Next, the number of cycles (training periods) for these 4 neurodes, with minimum error was identified. The number of cycles tested ranged from 50 to 250. The error was observed to decrease with increase in number of cycles and the minimum error was exhibited by 200 cycles. Hence, 4 neurodes for 200 cycles were chosen as the architecture for this neural network analysis (extrapolation to 35,000 h). Using this architecture, with the optimized adjustable parameters, the behavior of the system under consideration is again generalized.

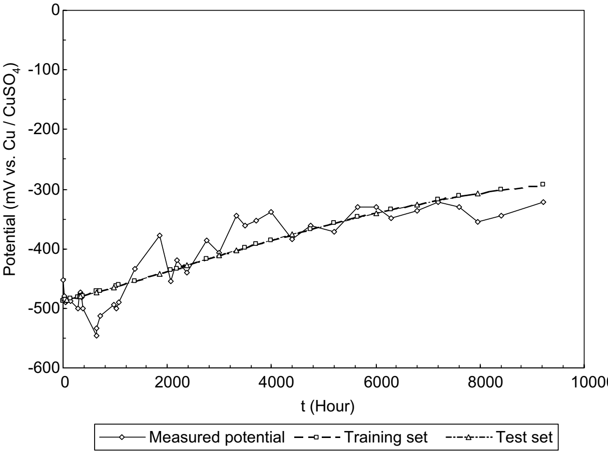

Fig. 13. Validation of test data set with the training data set and experimental values for slab 2.

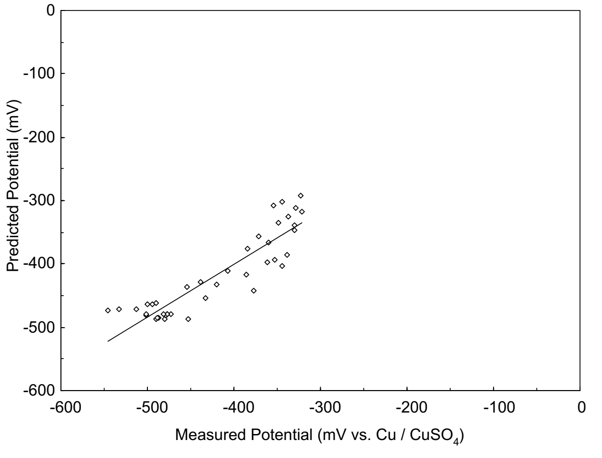

Fig. 14. Correlation between the predicted potentials and measured potentials for slab 2.

Fig. 15 compares the predictions made by the neural network with the data for training from two different sets. One set of training data was taken from the measured data up to 10,000 h and the other set of training data was taken from the measured data up to 28,600 h. From the figure it can be clearly seen that the training data chosen from 28,600 h yields a more reliable network architecture than the other set.

For slabs 1 and 2 the network was generalized with an input layer, one hidden layer (with optimum number of neurodes evaluated for each set) and an output layer.

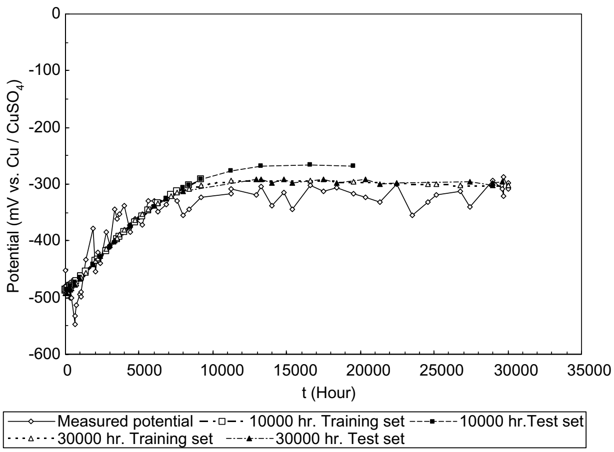

Fig. 15. Comparison of the predictions made with the data for 10,000 and 28,600 h for slab 2.

4. Conclusions

From the above observations and discussions, the following conclusions can be drawn for the less probable corroding system (slab 1) and the more probable corroding system (slab 2).

The data obtained correlated well with respect to the prevailing/expected conditions. They indicated that the steel in slab 1 exists in the zone of 90% probability for no corrosion while that in slab 2 exists in the zone of 90% probability for corrosion, as per ASTM C-876-91 (1999).

The neural network analysis adapted for these systems, were able to recognize the behavior of the systems. The behavior was observed to be very similar to that observed experimentally. The fitting between the calculated and the measured values was observed to be considerably high.

The predictions that were made based on the recognized pattern were observed to correlate well with the experimentally observed behavior.

However, the correlation varied depending on the range of data selected for training. It was observed that a shorter range of data could predict over a relatively smaller range for extrapolation. When the range of training data was extended, the prediction was also becoming possible over a longer range, with higher accuracy.

ANNs have been shown to be a feasible strategy for data analysis. ANNs used in this study enables the calculation of potential data which are in close agreement to experimentally obtained potential data for the test system which was used in this study. ANNs showed higher flexibility and were less complex in modeling and optimization. ANNs, in mathematical sense, are equivalent to a function of several variables, although the variables may not have definite relationships among themselves.

Further work is in progress to understand the application of ANN for analyzing the data based on variations in resistivity, grades of concrete etc.

References

[1] J.H. Hoke, H.W. Pickering, K. Rosengarth, Cracking of Reinforced Concrete, ILZRO Project ZE 271, Progress Report 3, Department of Materials Science and Engineering, Pennsylvania State University, University Park, PA, May 1980.
[2] A. Sagüés, S.C. Kranc, B.G. Washington, Computer modelling of corrosion and corrosion protection of steel in concrete, in: R.K. Dhir, M.R. Jones (Eds.), Concrete 2000—Economic and Durable Construction Through Excellence, E. and F.N. Spon, London, 1993, p. 1275.
[3] D.A. Hausmann, Mater. Perform. (Oct. 1998) 64.
[4] A. Steffens, D. Dinkler, H. Ahrens, Cement Concrete Res. 32 (6) (2002) 935.
[5] S.C. Kranc, Alberto A. Sagüés, Corros. Sci. 43 (7) (2001) 1355.
[6] F. Schmidt-Döhl, F.S. Rostásy, Cement Concrete Res. 29 (7) (1999) 1047.
[7] M. Böhm, J. Devinny, F. Jahani, G. Rosen, Appl. Math. Comput. 92 (2–3) (1998) 247.
[8] V. Feliu, J.A. González, C. Andrade, S. Feliu, Corros. Sci. 40 (6) (1998) 975–993.
[9] V. Feliu, J.A. González, C. Andrade, S. Feliu, Corros. Sci. 40 (6) (1998) 995.
[10] T. Liu, R.W. Weyers, Cement Concrete Res. 28 (3) (1998) 365.
[11] J.G.M. Wood, J. Crerar, Construct. Build. Mater. 11 (4) (1997) 249.
[12] P. Arora, B.N. Popov, B. Haran, M. Ramasubramanian, S. Popova, R.E. White, Corros. Sci. 39 (4) (1997) 739.

[13] J. Padov, J. Jin, Eng. Fract. Mech. 56 (6) (1997) 797.
[14] S. Prudil, Cement Concrete Res. 7 (1) (1977) 77.
[15] ASTM C 876-91 (1999).
[16] CEN Standard, Final Draft pr EN 12696-1.
[17] Department of Energy, Offshore Technology Report: Development of inspection techniques for reinforced concrete, Concrete in the oceans series, HMSO, London, 1986.
[18] D.J. Amit, Modeling Brain Function, The World of Attractor Neural Networks, Cambridge University Press, Cambridge, 1989.
[19] I. Aleksander, H. Morton, An Introduction to Neural Computing, Chapman and Hall, London, 1990.
[20] R. Beale, T. Jackson, Neural Computing: An Introduction, Adam Hilger, Bristol, 1990.
[21] R.C. Eberhart, R.W. Dobbins, Neural Network PC Tools: A Practical Guide, Academic Press, New York, 1990.
[22] G.A. Carpenter, S. Grossberg, Pattern Recognition by Self-Organizing Neural Networks, MIT Press, Cambridge, MA, 1991.
[23] A.M. Bose, W.E. Van der Linden, Anal. Chim. Acta 256 (1992) 133.
[24] J.W. Ball, P.C. Jurs, Anal. Chem. 65 (1993) 505.
[25] J.A. Freeman, D.M. Skapura, Neural Networks: Algorithms, Applications and Programming Techniques, Addison-Wesley Publishing Company, 1992.
[26] M. Defernez, E.K. Kemsley, Analyst 124 (1999) 1675.
[27] S. Gang, Z. Yongyao, W. Huaiwen, C. Hongli, C. Xingguo, H. Zhide, Analyst 125 (2000) 921.
[28] Q. Li, X. Yao, X. Chen, M. Liu, R. Zhang, X. Zhang, Z. Hu, Analyst 125 (2000) 2049.
[29] M.Y. Rafiq, G. Bugmann, D.J. Easterbrook, Comput. Struct. 79 (17) (2001) 1541.
[30] A. Kaveh, H. Servati, Comput. Struct. 79 (17) (2001) 1561.
[31] J. Cai, S.B. Lyon, R.A. Cottis, Corros. Sci. 41 (10) (1999) 2001.
[32] R.A. Cottis, M. Turega, Final report on neural networks for corrosion engineering, EPSRC grant number J48481, UMIST, Manchester, UK, 1997.
[33] M. Gower, S. El-Belbol, Monograph 4, Corrosion Protection Association, UK, 2002.