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Neural Network Mapping of Corrosion Induced Chemical Elements Degradation in Aircraft Aluminum

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Abstract: A neural network (NN) model is developed for the analysis and prediction of the mapping between degradation of chemical elements and electrochemical parameters during the corrosion process. The input parameters to the neural network model are alloy composition, electrochemical parameters, and corrosion time. The output parameters are the degradation of chemical elements in AA 2024-T3 material. The NN is trained with the data obtained from Energy Dispersive X-ray Spectrometry (EDS) on corroded specimens. A very good performance of the neural network is achieved after training and validation with the experimental data. After validating the NN model, simulations were carried out to obtain the trends in element degradation with varying pH values, and the results showed correct trends. The preliminary results obtained demonstrate that through a comprehensive study, a better corrosion resistant material can be designed by controlling the degradation of the chemical elements during the corrosion process through neural network methods.

Keyword: Al alloys, EDS, Pitting corrosion, Neural networks, Computational simulations

1 Introduction

General corrosion and especially pitting corrosion is known to be one of the major damage mechanisms affecting the integrity of many aerospace metals. Corrosion pits generally initiate due to some chemical or physical heterogeneity at the surface, such as inclusions, second phase particles, flaws, mechanical damage, or dislocations. The aircraft aluminum alloys contain numerous constituent particles, which play an important role in corrosion pit formation [Wallace and Hoeppner (1985)]. To better understand particle-induced pitting corrosion in 2024-T3 and 7075-T6 aluminum alloys, optical microscopy, Scanning Electron Microscopy (SEM) and Transmission Electron Microscopy (TEM) techniques have been used [Wei, Liao and Gao (1998)]. Due to an aircraft's special service environments (e.g. salt water), electrochemical reactions are possible and corrosion pits are readily formed between the constituent particles and the surrounding matrix in these alloys. It is well known that corrosion pitting has a strong effect on the fatigue life of aluminum alloys used in aircraft structures [Wei, Liao and Gao (1998); Hoeppner (1979); Simon, Khobaib, Matikas, Jeffcoate and Donley (2000)]. Fatigue cracks usually initiate from the corrosion pit sites. Under the interaction of cyclic load and the corrosive environment, cyclic loading facilitates the pitting process, and corrosion pits, acting as geometrical discontinuities, lead to crack initiation and propagation and then final failure [Harmsworth (1961); Piascik and Willard (1994); Wei, Liao and Gao (1998); Jones and Hoeppner (2006)]. Corrosion can lead to accelerated failure of structural components under fatigue loading conditions. Understanding and predicting corrosion damage is very important for the structural integrity of aircraft materials and structures.

Many researchers have studied pitting corrosion for several decades and the details can be found in several books [Marcus and Oudar (1995); Shreie, Jarman and Burstein (1994); Harlow and Wei (1998)]. Many aluminum and stainless steel alloys contain thin oxide layers on the metal surface which greatly reduce the corrosion rate. Pitting corrosion, a result of localized breakdown of

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Table 1: Elemental composition of the AA 2024-T3 specimens tested

Element	Element Symbol	Atomic Weight	Oxidation #	Mass Percent (%)
Aluminum	Al	26.985	3	93.0
Copper	Cu	63.456	2	4.50
Magnesium	Mg	24.305	2	1.45
Manganese	Mn	54.938	2	0.57
Iron	Fe	55.847	3	0.25
Silicon	Si	28.085	4	0.11
Zinc	Zn	65.38	2	0.09
Titanium	Ti	47.90	3	0.02
Chromium	Cr	51.996	4	0.01

such films, results in accelerated dissolution of the underlying metal. The corrosion mechanisms depend on the material composition, electrolyte and other environmental conditions [Shreie, Jarman and Burstein (1994); Harlow and Wei (1998)]. Most of the previous work on corrosion has been focused on chemical processes and electric currents and potentials, and simulations models [Harlow and Wei (1998); Palakal, Pidaparti, Rebbapragada and Jones (2001); Malki and Baroux (2005); Pidaparti, Palakal and Fang (2005)]. Several authors have applied other methods such as boundary element methods [Aoki, Amaya, Urago and Nakayama (2004)] and cellular automata [Pidaparti, Puri, Palakal and Kashyap (2005)] for corrosion problems. Neural Networks (NN) has also been applied to pitting corrosion [Lu and Urquidi-Macdonald (1994)]. Even though ANN doesn't contain any empirical or deterministic models or explain the physics of the localized corrosion, it is still being used to predict future behavior with various parameters.

Pitting corrosion is a very complex process and may involve many mechanisms. While much is understood regarding corrosion damage from electrochemical factors, and alloy microstructure, there are no studies dealing with the modeling of chemical elements degradation due to corrosion in aircraft aluminum alloys (AA). For the past few years, the first author has been studying the structural integrity and durability issues related to aging aircraft materials and structures. The present project is aimed at developing computational simulation models to investigate the evolution of chemical elements degradation in the corrosion process. The developed algorithms supported by experiments might be useful for manipulating various parameters for material design applications.

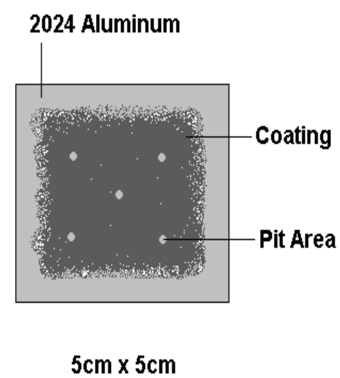

Figure 1: Typical specimen of AA 2024-T3 used in electrochemical experiments for corrosion

The objective of this study is to develop a neural network (NN) model for the analysis and prediction of the mapping between degradation of chemical elements and electrochemical parameters during the corrosion process. Experimental data obtained from controlled electrochemical conditions on AA 2024-T3 specimens along with the chemical element degradation data obtained through EDS technique were used for training and testing of the neural network model. The nonlinear relationship between the chemical elements degradation and material loss as a function of time was studied using the developed neural network.

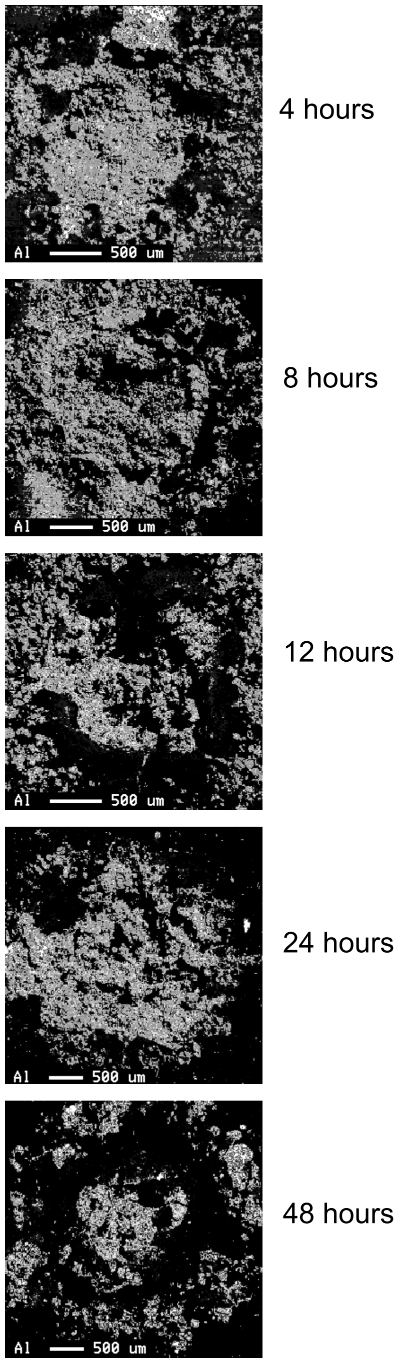

Figure 2: Degradation of aluminum material over a specimen corroded at 4, 8, 12, 24, and 48 hours

2 Experiments

AA 2024-T3 (5 x 5 cm in size, 1.5 mm thick) alloy specimens precut from a 12" x 12" sheet were used in electrochemical experiments to systematically corrode over pre-specified times. The nominal composition of chemical elements in AA 2024-T3 along with their atomic weight is given in Table 1. All samples were coated with nail polish except for small circles where corrosion is allowed to take place as shown in Fig. 1. A solution of sodium chloride (NaCl) was prepared using sodium chloride crystals and deionized water. A stirrer was used to thoroughly mix the sodium chloride with the deionized water. Electrochemical measurements were conducted using the GAMRY-Electrostatic Potential-Potentiostatic Instruments PC3/300 potentiostat/galvanostat/ZRA with Framework (version 3.11) and DC 105 program. Once all the electrodes are placed correctly on various part of the electrochemical cell, the GAMRY-Electrostatic Potential-Potentiostatic was run. All the experiments were conducted at room temperature. Several specimens were corroded for a variety of durations ranging from 1 hr to 48 hrs in 2 molar NaCl electrolyte solution. For each time step, the material loss and corrosion rate is obtained from the program.

Energy Dispersive X-ray Spectrometry (EDS) was used to determine the chemical elements present after corrosion through point analysis and elemental mapping on corroded specimens. A typical chemical element map obtained for Al element at various times of corroded specimens from EDS is shown Fig. 2. Table 2 shows the original data of counts per second of all the alloy elements in AA 2024-T3 was obtained from EDS measurements on corroded specimens at various times. This data was used in developing the neural network model.

3 Neural Network Modeling

The objective here is to develop neural network models to map degradation of the chemical elements in aircraft aluminum (AA 2024-T3) with various electro-chemical parameters during the

Table 2: Chemical elemental degradation data (normalized from point counts/sec) of the AA 2024-T3 corroded specimens using EDS technique

Time (hrs)	Al	Cl	Ba	O	C	Cu	S	% Material Loss
0	1	1	1	1	1	1	1	0.00
4	0.61	0.89	0.65	0.6	0.77	0.6	0.8	35.42
6	0.43	0.86	0.6	0.5	0.67	0.45	0.75	49.73
8	0.29	0.89	0.56	0.45	0.56	0.33	0.66	60.77
12	0.15	1	0.28	0.4	0.33	0.17	0.5	74.00
14	0.13	0.95	0.25	0.38	0.3	0.15	0.45	76.43
18	0.12	0.8	0.23	0.36	0.26	0.14	0.35	79.00
20	0.11	0.7	0.22	0.35	0.25	0.13	0.31	80.62
22	0.11	0.68	0.22	0.33	0.23	0.12	0.27	81.33
24	0.11	0.67	0.2	0.33	0.22	0.11	0.25	81.70
26	0.1	0.67	0.19	0.31	0.22	0.09	0.25	82.68
28	0.1	0.67	0.18	0.3	0.22	0.07	0.25	82.92
48	0.09	0.67	0.17	0.23	0.22	0.06	0.25	84.41

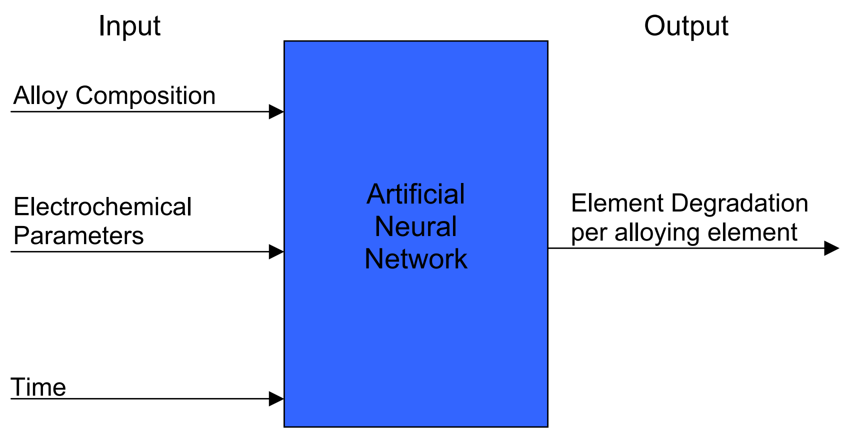

Figure 3: Schematic model of artificial neural network for prediction of degradation behavior due to metal corrosion

corrosion process. A brief summary the neural network approach is given below.

3.1 *Neural network basics*

Neural networks (NNs) are intelligent arithmetic computing elements that can represent complex functions with continuous-valued as well as discrete outputs, and large number of noisy inputs, by learning from examples [Russell and Norvig (1995); Anderson and McNeill (1992); Aleksander and Morton (1995); Principe, Euliano and Lefebvre (2000); Beale and Jackson (1990); Orchard (1991); Swingler (1996); Bulsari and Kallio (1995)]. The network uses systems of non-linear basis functions to relate the input to the desired output as shown in Fig. 3. Because of the use of these non-linear functions and the statistical nature of the model, neural networks can be applied to solve a variety of problems that are not possible with analytical methods. Although the idea of neural networks has been around for some time, it has undergone a recent surge of usage in many fields from medical to material science [Principe, Euliano and Lefebvre (2000); Beale and Jackson (1990); Bulsari and Kallio (1995)].

Neural Networks consist of arrays of processing

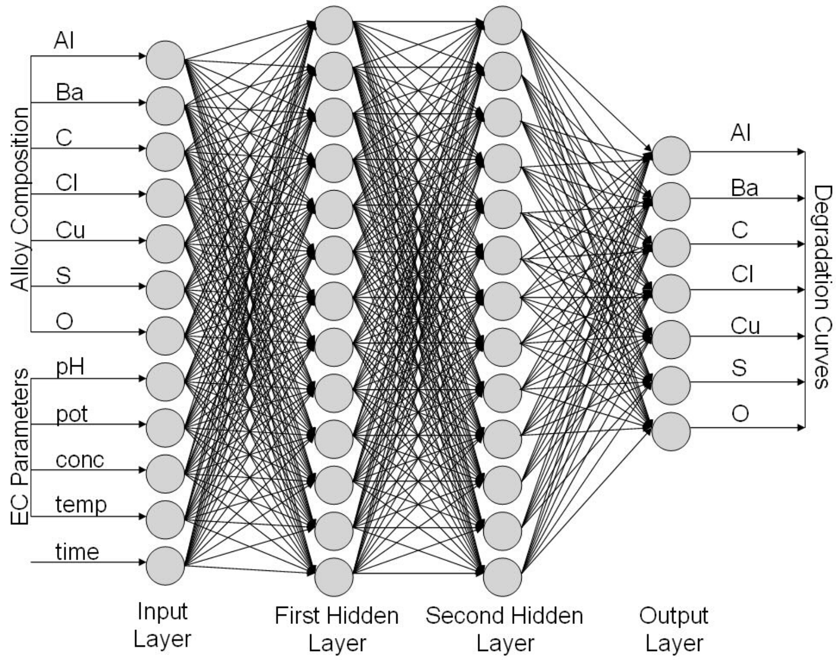

Figure 4: Neural Network Architecture developed for the analysis and prediction of chemical element degradation behavior during the corrosion process

elements called neurons or nodes. The neurons are arranged in layers that process that data as its passes through the network. The neurons are interconnected through links called synapses. Each synapse is given a weight factor that is determined after the network is trained. Weights are the primary means of long-term storage in neural networks, and learning usually takes place by updating these weights. The weights are adjusted so as to bring the network's input/output behavior more in line with that of the phenomena being modeled by the network. There are multiple types of network architectures. The most popular method for learning in multi-layer networks is called back-propagation, which was first invented by Bryson and Ho in 1969. More details about the neural networks and their concepts can be found in Ref. [Russell and Norvig (1995)].

3.2 Neural network architecture

In this study, a multi-layer, feed-forward neural network with back-propagation learning algorithm is developed to investigate the degradation of chemical elements due to corrosion process in aircraft aluminum. Figure 4 illustrates the architecture of the developed network for mapping chemical degradation during the corrosion process. The input parameters to the neural network model are alloy composition, electrochemical parameters, and time. The composition includes the most commonly present elements in structural grade aluminum alloys. The electrochemical parameters inputted include the pH value at the time of corrosion, the electrolyte concentration, the corrosion potential, and the temperature. Each of these parameters is assumed and held constant over time. The desired duration of the corrosion simulation is also inputted in hours. The outputs of the neural network are the degradation amount of each alloying element inputted.

The neural network model developed in this study is intended to be capable of analyzing multiple alloys with various chemical elements in their composition. Currently, the network is capable of analyzing a single aluminum alloy, namely, AA 2024-T3, which is commonly used structural alloy in the aerospace industry. The model inputs the seven elements (Al, Ba, C, Cl, Cu, O, and S) that make up the AA 2024-T3 alloy. The four electrochemical parameters are inputted along with time. Altogether there are 12 input nodes for the created network. The current neural network model has 2 hidden layers having 15 nodes each. This configuration was reached after a few iterations of a single hidden layer network proved to give less than adequate results [Swingler (1996)]. For the seven alloy elements, there are seven output nodes. Each outputs the degradation curve of one of the alloying elements. Therefore, a 12-15-15-7 neural network architecture was developed and trained and tested to validate the model.

3.3 Neural network training and testing

A neural network is usually trained using a large dataset of input/output pairs. In this study, experimental datasets obtained from EDS imaging techniques was used to train the network using a back-propagation algorithm, specifically the batch gradient decent function (traingd) [Aleksander and Morton (1995); Principe, Euliano and Lefebvre (2000); Swingler (1996)]. Each of the input variables is normalized so that all the data lie between 0 and 1, which is recommended for proper training of neural networks [Beale and Jackson (1990)].

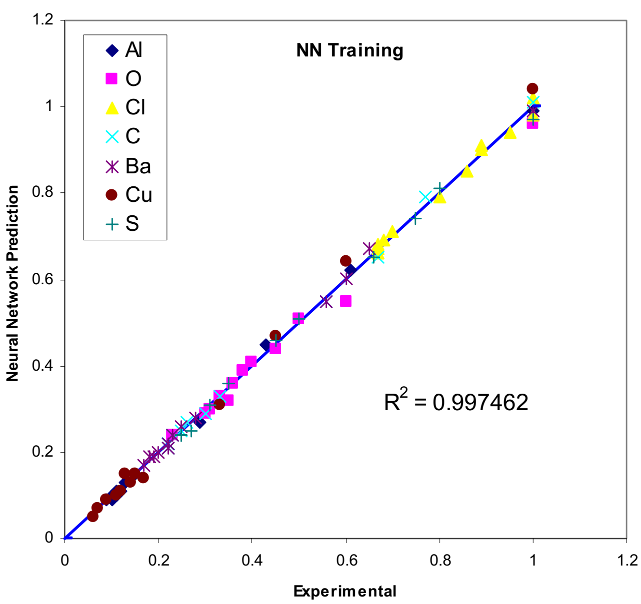

Figure 5: Comparison of NN predictions and the experimental data after training the network

For computer implementation, we have used the Matlab tool box due to its graphics capabilities. The feed-forward network was created with the 'newff' function. There are many transfer functions available in MATLAB software. After some experimentation with "tansig" and "logsig" transfer functions, the "logsig" transfer function was chosen due to nature of the output desired in the neural network modeling. The learning rate was set reasonably low at 0.05 to ensure convergence of the algorithm. Number of epochs was set at 500 and a convergence goal of 1e-5 was used. A database was constructed by collecting experimental data from EDS measurements and processing it to the input/output required from the network. In total, 91 pairs of input/output data was used for NN training. We realize that this data set is not very large, but we believe it is sufficient to develop a converged network for the inputs specified. A set of experimental data obtained in section 2 was set aside for validating/testing the developed neural network.

4 Results and Discussion

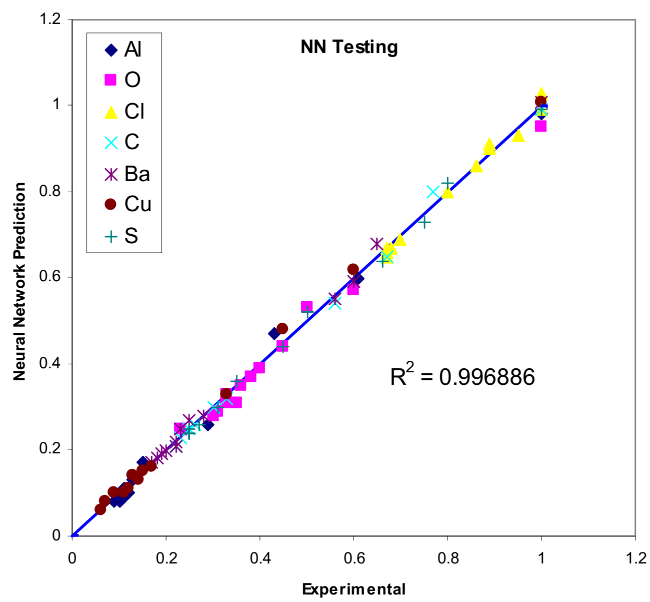

Figure 6: Validation and testing of NN predictions with the experimental data after training the network

The performance of the neural network was validated after training the network. Figure 5 shows the comparison of results between NN predictions and the experimental data after training the network. Most of the elements are trained well to the experimental data. It can be seen from Fig. 5 that a good correlation is obtained between the NN predictions and the experimental data with a correlation coefficient of 0.9974.

To test/validate the generalization performance of the trained NN in capturing the degradation behavior, the NN predicted values along with experimental data that was not used in training are shown in Figure 6. A very good agreement was found between the predicted values from the trained neural network and the experimental data with a correlation coefficient of 0.997. Testing proved that the network could reproduce the behavior for a set of data not used in the training process. This testing also demonstrates that neural networks should be able to extract the relationship and rules and then apply these rules to obtain reasonable predicted results.

Further validation and testing was performed to see how the trained network could handle situations that are within or outside the range of trained data. This includes interpolation and extrapolation of the alloy element degradation behavior during the corrosion process. The NN predicted results are compared in Figs. 7 and 8 along with the experimental data. It can be seen from Figs. 7 and 8 that the trained network was able to capture the degradation behavior within and outside the range of trained experimental data and portray trends accurately. These validations are further testimony that the developed neural network was able to predict the degradation behavior reasonably well.

In order to observe the effects of the various input electro-chemical parameters on the degradation behavior, several cases can be simulated using the trained neural network. The effect of changing other electrochemical parameters was examined but due to lack of training involving the variation of these parameters no change was noted in the neural network prediction. However, since pH is very sensitive as compared to other electrochemical parameters in the corrosion process [Pidaparti, Palakal and Fang (2005)], a simulation experiment was conducted by retraining the neural network. Based on the experimental observations and data in the literature [[Marcus and Oudar (1995); Shreie, Jarman and Burstein (1994); Harlow and Wei (1998)], a pH of 7 which is neutral is not going to affect the specimen corrosion. With

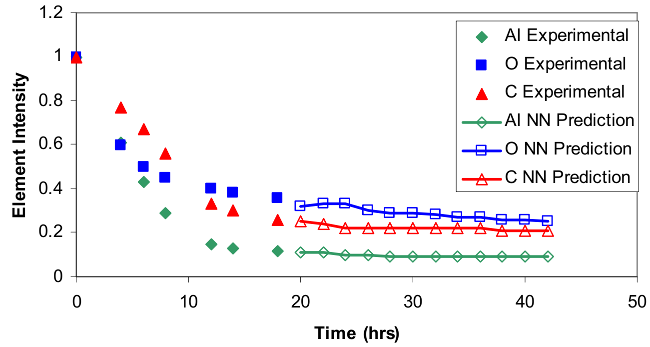

Figure 7: Further testing of NN predictions with the experimental data (extrapolation)

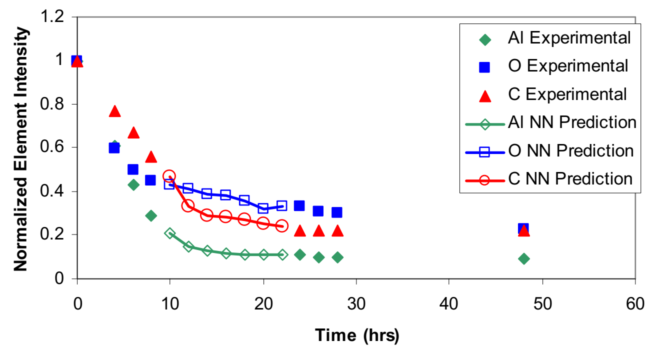

Figure 8: Further testing of NN predictions with the experimental data (interpolation)

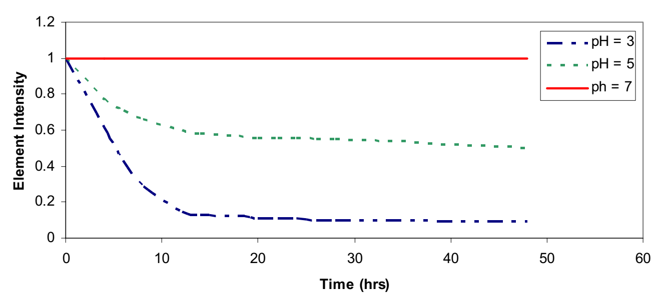

Figure 9: Effect of acidic pH change on degradation behavior of aluminum element obtained from NN simulation

this knowledge a second dataset was created for a pH value of 7 that contained no corrosion. It is also known that high basic pH values will exhibit corrosion. To train the network for this behavior a third dataset was created using the existing data for a pH of 3 and setting the input pH to 11, due to lack of any other data. The network was further trained with the two datasets to introduce the behavioral change due to pH variation. The effect of changing pH on the degradation behavior is shown in Figure 9. It can be seen from Fig. 9 that the NN predicts the correct trends with varying pH values in the model. However, more experimental data is needed for further analysis and prediction. Overall, the results presented in Figs. 7-9 demonstrate the use of neural networks for the analysis and prediction of chemical element degradation during the corrosion process.

5 Summary and Conclusions

A neural network model is developed for the analysis and prediction of the mapping between degradation of chemical elements and the electrochemical parameters during the corrosion process. The NN model is validated and tested with data obtained from Energy Dispersive X-ray Spectrometry (EDS) measurements on corroded specimens at various times. The results obtained from the study indicate that overall, the neural network predictions compared reasonably well with the experimental data obtained. Simulations were carried out to obtain the trends in element degradation with varying pH values, and the results showed correct trends. The preliminary results obtained demonstrate that through a comprehensive study with more experimental data, a better corrosion resistant material can be designed by controlling the degradation of the chemical elements during the corrosion process using the developed neural network model.

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