# SIMULATION OF THE EFFECTS OF POZZOLANIC ADDITIVES AND CORROSION INHIBITOR ON THE CORROSION OF REINFORCED CONCRETE BY ARTIFICIAL NEURAL NETWORKS

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***In this research, we simulate the corrosive behavior of steel reinforcements on 5 different mixtures to investigate the effect of two powerful protective methods, including pozzolanic additives and corrosion inhibitor on concrete, by artificial neural networks (ANNs).***

***Related to this model, fly ash (FA), micro silica (MS), and slag were used as pozzolanic materials at an optimum 25%, 10%, and 25% of cement weight, respectively. Moreover, Ferrogard 901 as an inhibitor was also utilized. The producer recommends using12 kg/m$^3$ to get the best possible results. The non-linear corrosion of concrete into a marine solution (3.5% NaCl) was simulated by the feed forward back propagation (FFBP) algorithm. Data acquisition happened over a period of 180 days, and according to the ASTM C876 standard for simulating harsh conditions, a period of 10 years was selected as the simulation period. The simulated results all align with collected data. The mixture with 10% of MS has the lowest corrosion current density and corrosion rate at the end of 3600 days, which are 0.38 µA/cm$^2$ and 0.20 mpy, respectively. It provides the best protection against reinforcement corrosion.***

**Keywords:** *pozzolanic concrete, inhibitor, corrosion, simulation, artificial neural networks*

## 1. Introduction

Money has been spent each year for reinforcement corrosion in concrete marine structures and this has always been a challenge for researchers [1]. One of the best and most economical approaches to reduce the corrosion of steel in concrete is to use pozzolanic concrete [2, 3]. Pozzolanic materials are usually introduced as silica or alumina silicate compositions to reduce concrete permeability and increase compressive strength, durability, resistance, and the adhesion properties of concrete [4-6]. In recent years, fly ash (FA), micro silica (MS) and slag, with a $Ca(OH)_2$ activator, have been identified as efficient and applicable pozzolanic materials used in adverse researches and field structures [7, 8]. Moreover, corrosion inhibitor admixtures are also used as a powerful and economic alternative in a concrete grouping as anodic, cathodic, and mixed admixtures owning to the simultaneous effect on both anodic and cathodic corrosion reactions with greater application in the concrete industry. To appraise and simulate concrete durability and strength, there are various computational analysis techniques [9, 10] in which the artificial neural networks (ANNs) analysis is one of the most known [11-13]. This technique has been introduced for corrosion simulation [17] in offshore structures. Hong et al. predict the compressive strength of concrete with a 28 days curing time by multi-layer feed forward neural networks (MFFNNs). Results illustrated that the ANNs models demonstrate high prediction accuracy and can be practically used to predict the strength properties of concrete [18]. Furthermore, ANNs offer insights regarding the prediction of the compressive strength of steel fiber embedded in lightweight concrete, and the acquired outcomes in comparison with the multi-layer regression technique revealed a more accurate data [19]. By focusing on the corrosion concept, Topca and coworkers simulated the concrete corrosion current density and mechanical properties through the FA in addition to mixing design by the feed forward artificial neural networks. Measured results were then evaluated with the Root Mean Square Error (RMSE), the Mean Absolute Percentage Error (MAPE), and the correlation coefficient criterion. Using composite cement or FA instead of cement could considerably improve the durability of concrete, and, on the other hand, ANNs analysis can be utilized as an accurate model for corrosion current density simulation in concrete [20].

Ukrainczyk and coworker utilized ANNs to model the durability of reinforced concrete

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damage analysis [14-16] and

structures in marine and continental environments. A comparison of the two models based on the different environments was achieved. The proposed models were able to recognize and evaluate the effect of individual parameters on concrete damage and can also be utilized to predict protection and maintenance and estimate the service life of the structures [21]. Parthiban et al. also used neural network analysis to interpret the corrosion behavior of reinforced concrete. In the investigated system, the error is only about 5% for predictions made from the analysis [17]. Elsewhere, ANNs have been used as a tool to minimize uncertainties and errors of the proportioning of concrete mixes [22]. In addition, research has been carried out using ANNs to simulate concrete properties, such as hydration degree [23], compressive strength [24], and slump conditions[25]. To the best of our knowledge, there is a restricted understanding of the precise electrochemical simulation of rebar in concrete. In this study, the effect of a more efficient corrosion reducer, such as pozzolanic materials and inhibitor admixture, was simulated. MS, FA and slag as pozzolanic materials in an optimum percent of cement 25, 10 and 25 respectively, and Ferrogard 901 as well as an inhibitor admixture were used. At 180 days, the corrosion current density and the potential of reinforced concrete immersed in 3.5% NaCl was measured by the polarization test and also the behavior of concrete for 10 years according to ASTM: C876 standard accompanied by MFFNNs and back propagation algorithm was predicted.

## 2. Material and methods

### *2.1 Concrete materials*

In this research, type II Portland cement was used to turning out of the concrete mixing design chemical composition of described cement according to ASTM: C150, FA type F in accordance with ASTM: C618 in the optimum amount of 25 % weight of cement [26], Semnan MS in the optimal content of 10% weight of cement [27] and slag in the best weight (25% wt.) [28] of cement, as demonstrated in Table 1.

The composition of the Ferrogard 901 admixture, which served as a mixed inhibitor in the supplier proposed content with approximately 12 kg/m$^3$ of concrete, are characterized in table 2.

### *2.2 Preparing the concrete mixture*

The mild carbon steel rebar (A 20), with 12mm diameter and a 250 mm height embedded in the concrete centerline as reinforcement and stainless steel 304 sheets with a dimension of about 15×210 mm in 20 mm distance of the rebar was used as a counter electrode. The rebar bottom and the interface position of the rebar and the mortar in the concrete external face was carefully painted with epoxy and was then covered by insulator tape to prevent from the crevice and the atmospheric corrosion of reinforcement in the 3.5% NaCl solution. To have a one dimensional diffusion of chloride ions from the radius of the cylinder concrete bottom and the upper surface, all concrete is precisely coated with a wax layer. Figure 1 schematically illustrates the reinforcement concrete samples.

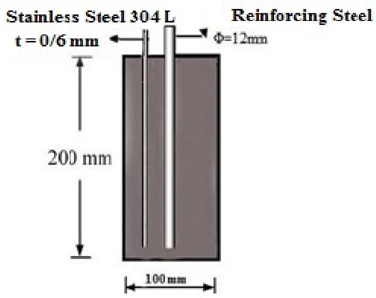


Fig.1 - Schematic of the concrete specimen.

In this study, the main strategy is to compare the corrosion behavior of concrete containing 0.4 water to cement (w/c) proportion as a control specimen regarding four other mortar mixing design which in each, one additive, such

**Table 1**

Chemical composition of cement type II, FA, MS and Slag

| Chemical composition ,% | Cement type II | *FA* | MS | Slag |
|---|---|---|---|---|
| CaO | 62 | 4.62 | 3 | 34.2 |
| $SiO_2$ | 21 | 51.5 | 94 | 66.39 |
| $Al_2O_3$ | 3.3 | 30.5 | 0.4 | 12.94 |
| $Fe_2O_3$ | 1.5 | 6.7 | 0.7 | 1.58 |
| MgO | 5.5 | 3 | 0.1 | 6.94 |
| $SO_3$ | 1.7 | 0.4 | 0.15 | 0.72 |
| $Na_2O$ | 0.14 | 0.43 | 0.23 | 0.2 |
| $K_2O$ | 0.64 | 0.55 | 0.44 | 1.44 |
| Cl | 0.012 | 0.007 | 0.002 | 0 |

**Table 2**

Chemical admixture of Ferrogard 901

| Name | Chemical Composition | Color | Density (kg/l) | pH | T ($^o$C) |
|---|---|---|---|---|---|
| Sika Ferrogard901 | Dimethyl amino ethanol | Green | 1.06 | 10 | 1-35 |

**Table 3**

Mixing design content

| Component | Mix Design | | | | |
|---|---|---|---|---|---|
| | NO. 1 | NO. 2 | NO. 3 | NO. 4 | NO. 5 |
| Cement (g) | 400 | 400 | 400 | 400 | 400 |
| W/C | 0.4 | 0.4 | 0.4 | 0.4 | 0.4 |
| Sand (g) | 823 | 823 | 823 | 823 | 823 |
| Fine aggregate (g) | 400 | 400 | 400 | 400 | 400 |
| SP (g) | 1 | 1 | 1 | 1 | 1 |
| Inhibitor (ml) | - | 2 | - | - | - |
| MS (g) | - | - | 40 | - | - |
| FA (g) | - | - | - | 100 | - |
| Slag (g) | - | - | - | - | 100 |

as MS, FA, slag and Ferrogard 901, has been used in the best percentage to minimize the corrosion current density of rebar in concrete. Concrete mortars were cured in water to complete the hydration reactions for 14 days in more than 90% RH and room temperature. Double-washed sand, 4.5 to 9 mm size, have also been utilized as aggregation. Table 3 summarizes mixing design data.

### 2.3 *Electrochemical experiment*

To evaluate corrosion behavior and measure the corrosion current density, potential, and corrosion rate, the polarization test was used. The polarization curves were measured with potentiostat/galvanostat Model 273A (EG&G Co.) and SoftCorrTM252/352 corrosion software. A 300 mv cathodic and anodic over potential were applied at the opposite to open circuit potential (OCP) of the rebar in concrete with a scan rate of about 0.16 v/s. The corrosion current density and potential were measured using the linear polarization method for a period of 180 days. During this period, every five days two samples with the same condition were examined to improve accuracy.

The polarization test was carried out along with 3 electrode systems for which the rebar acts as a working electrode, the stainless steel sheet embedded in the mortar operated as counter electrode, and the reference electrode was saturated calomel electrode (SCE) with a lugging connection to reduce the uncompensated resistance of the solution.

### 2.4 *Simulation by ANNs*

One of the most ordinary ANNs is the Feed Forward Layer Neural Network, which usually has one or some layers between the input and output layers. These layers are called hidden layers. For learning ANNs in this study, the Levenberg-Marquardt algorithm was used. Simulations using the Back Propagation (BP) Neural Network have been used. This algorithm is a powerful approach to anticipate the high strength concrete manner with mineral or chemical additives [25]. For the first step, the input learning algorithm to the input layer was provided. The network releases the input algorithm layer-by-layer to calculate the output layer for
layer and one output layer concerning any of them an output algorithm.

The sigmoid function assigned as transfer relation derived from Eq 1.

$$O_i=1/(1+e^{-gi}) \quad (1)$$

Where $O_i$ is predicted value. After training the network, the predicted and experimental values are compared with the root mean square error (RSME), the mean absolute percentage error (MAPE), and the correlation coefficient (R). RSME, MAPE, and R are calculated by following formula.

$$RMSE=\sqrt{\frac{1}{n}\sum\left|t_i-o_i\right|^2} \quad (2)$$

$$MAPE=\left|\left(\frac{t_i-0_i}{0_i}\right)\right|\times 100 \quad (3)$$

$$R=\sqrt{1-\left(\frac{\sum\left|t_i-o_i\right|^2}{\sum\left|o_i\right|^2}\right)} \quad (4)$$

$t_i$ ,are the experimental values, $O_i$ are the predicted values, and P is the number of data [8, 29]. The MATLAB NN Tool Box was used. ANNs simulated the acquisition data followed by, the measured result compared to RMSE and the correlation coefficient. Learning the ANNs is a repetitive calculation, which means selecting the weigh coefficient, the error function getting minimum values.

**Table 4**

Neural network simulator model

| No. | Detail | Selection |
|---|---|---|
| 1 | Network architecture | Back propagation network |
| 2 | Number of input | 1 |
| 3 | Number of output | 5 |
| 4 | Number of neurons | 20-40 |
| 5 | Transfer function | Sigmoid |
| 6 | Learning rate | 0.1 |

In this study, using the neural network, the corrosion behavior of steel rebar in concrete is predicted for 3600 days. Each type of neural network has an input layer, one or some hidden

more or less similar to two other mixing design for has some neurons. The time interval was the only parameter. On the other hand, the corrosion current density, potential, and corrosion rate of mixtures were considered as output parameters. The details and characteristics of the designed neural network were depicted in Table 4.

## 3.Results and discussions

Experts suggested that the addition of pozzolanic materials instated of cement to concrete structures synchronous with pH decrement prevents oxygen entrance and humidity, which are essential for the corrosion cathodic reaction. Hence, the corrosion phenomena will be polarized [30]. Polarization experiments with the five aforementioned mixtures after 180 days of exposure in the 3.5%NaCl solution clearly illustrates that concrete made up of MS will have less corrosion compared with other mixtures. Indeed, the first result pointed out that MS could be the best protection against concrete corrosion. Based on Figure 2, it remarkably showed that the corrosion rate for MS concrete after 180 days will reach 0.18mpy. Based on the represented corrosion probability in Table 7, this corrosion rate demonstrates that the mixture is located in the moderate corrosion probability part of the table. This mixing design has perceptibly experienced a steady state condition compared with other samples. In other words, the relative sudden increment in the corrosion rate which was revealed in the other mixtures was not seen in the mixture with 10% MS, which can be attributed to filling the concrete porosity with MS particles and the completion of hydration reactions after about 120 days of being exposed to the salt environment. As a result, the thickness of the reinforcement in concrete will last for a longer period of time, meaning it will be more durable in this corrosive environment.

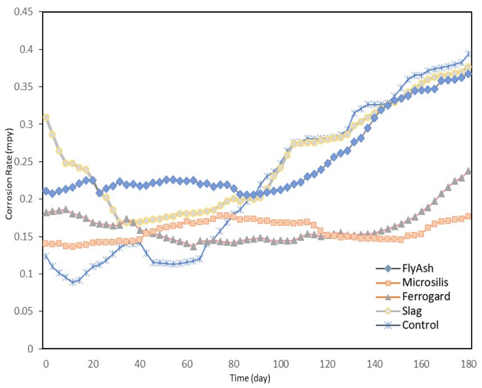


Fig. 2 - Corrosion Rate vs Time in 3.5% NaCl solution.

Figure 2 illustrates that the control sample, which is exposed to a corrosion rate of 0.4 mpy, has the highest corrosion rate, meaning it is the worst in protecting against corrosion. This value is slag and FA, respectively. The most prominent reason explaining this increment is owing to chloride ions diffusion from the solution through the concrete porosities (so FA and slag are less efficient at blocking open porosity in mortar) and reacting these free chloride ions with the passive layer on top of the steel rebar, after breaking down the above-mentioned barrier layer, the corrosion rate or corrosion current density suddenly increased. Indeed, these mentioned concretes, including control, slag, and FA, are in the high corrosion area, according to table 7 after approximately 120, 130 and 140 days of exposer in 3.5%NaCl respectively. Thus, during the period in which data was gathered, reinforcement was highly corroded and hence the prediction of the lifetime would be vividly less important compared with the MS and Ferrogard mixtures. For a better analogy, the outcomes of the corrosion potential are shown in Figure 3.

**Table 5**

**Corrosion current density criterion introduced by Rodriguez [35]**

| Corrosion Probability | Current Density ($\mu A/cm^2$) |
|---|---|
| Negligible | 0.1-0.2 |
| Low | 0.2-0.5 |
| High | 0.5-1 |
| Very High | >1 |

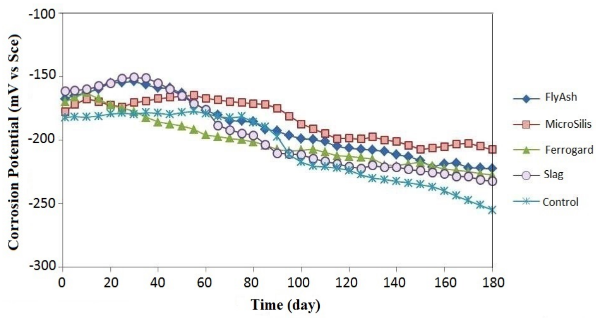


Fig. 3 - Corrosion Potential vs Time in 3.5% NaCl solution.

In accordance with ASTM: C876 and Figure 3, all 5 schemes after 180 days of exposure to the 3.5% NaCl solution are in the low corrosion range. However, it is explicitly perceived that this criterion is a thermodynamic prediction and could only explain the probability of the corrosion phenomena. On the other hand, the corrosion current density described earlier put forward a kinetic concept of rebar degradation so that data is certainly more reliable. In accordance with other research, completing the hydration reaction is a long-term process that takes about 80 to 90 days. During this period of time, the rebar potential will be gradually increased (a more positive value) corresponding to more stabilization of the passive oxide layer on steel surface in alkali environment.

Hence, the barrier layer will become slightly thicker and eventually will be destroyed and eliminated, as a result of exposure to chloride ions. Therefore, it will decrease the potential (a more negative value), and, as a result, corrosion will be increased [31]. Montomer's research demonstrate that after approximately 90 days the corrosion potential will reach a steady state. As a result, it is expected that after 90 days the passive layer of steel will be eradicated and steel corrosion will happen (transmission from passive to active state) in a constant potential (steady state corrosion potential) [32] . As shown in Figure 3, concrete with MS has the maximum corrosion potential and the best maintenance, and the reference concrete has the least corrosion potential and the lowest maintenance. Slag, FA and Ferrogard 901 lie between MS and the reference mixing design. Observations are nearly in good accordance with those generated by the corrosion current density experiment. The corrosion current density was precisely computed from equation 2 [33] and illustrated in Figure 4.

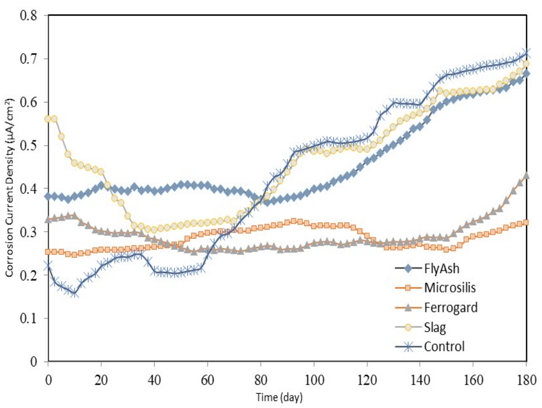


Fig. 4 - Corrosion Current Density vs Time in 3.5% NaCl solution.

$$C.R=0.129i/D \qquad (5)$$

Where C.R indicates the corrosion rate (mpy; millimeter/year), i is the corrosion current density of the embedded rebar in concrete ($\mu A/cm^2$), and eventually D explains the density of the steel in mortar (7.8 $g/cm^3$).

As can be seen, the reference concrete has the maximum corrosion current density, which is in the high corrosion probability, according to table 5, while the mixture containing 10% MS again has the minimum one and is located in the low corrosion probability zone. The concrete containing Ferrogard 901 is also in the low probability zone. It is the second best mixture in terms of corrosion resistance because it has the second lowest corrosion current density, which is the result of the protection layer around the reinforcement that has been formed by using Ferrogard 901.

After polarization, the experiment is implemented with ANNS for the behavior of steel

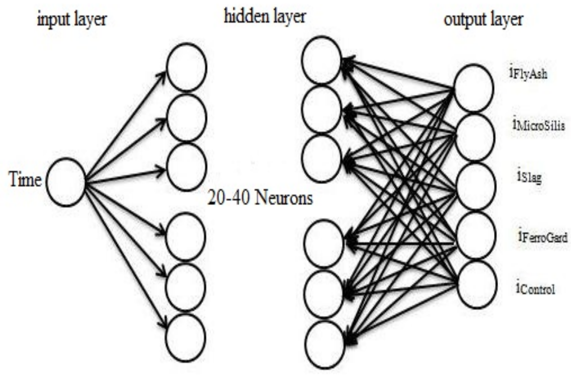


Fig. 5 - Schematically structure of the ANNs proposed model.

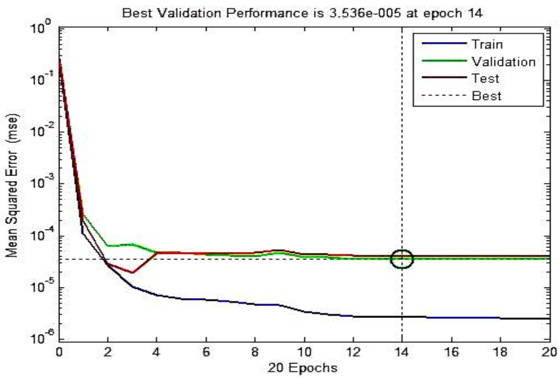


Fig. 6. -Corrosion rate trend curve error causal networks using learning algorithm.

corrosion, and is simulated for 3600 days. 70% of the 38 data points that existed for corrosion current density were for educated data, 15% were for authentication, and the remaining 15% were for experimental data. With three different networks, corrosion rate, current density, and corrosion voltage were simulated, and the time parameter was the only input variable. (Figure 5)

Figure 6 is the flow of the network using the LM educational algorithm to simulate the corrosion rate. As indicated in the figure, the MSE error will gradually decrease and after 20 iterations, the network education will face a Stop Validation message and so it will be stopped. This illustrates the decrease in authentication error collection, and the mass and biased are adapted to the time when this error was at a minimum. The similarity between the changes of error collection and authentication illustrates the desirable outcome.

In addition, for precise model analysis, the regression analyses between the output of the network and our evaluated ideal goals are reflected in Figure 7.

The closer the number is to 1, which illustrates low noise between data, the more a proper education network and an experiment via the means of the network will be obtained. The acquired correlation factor in anticipated corrosion current density simulation is above 0.99 and close

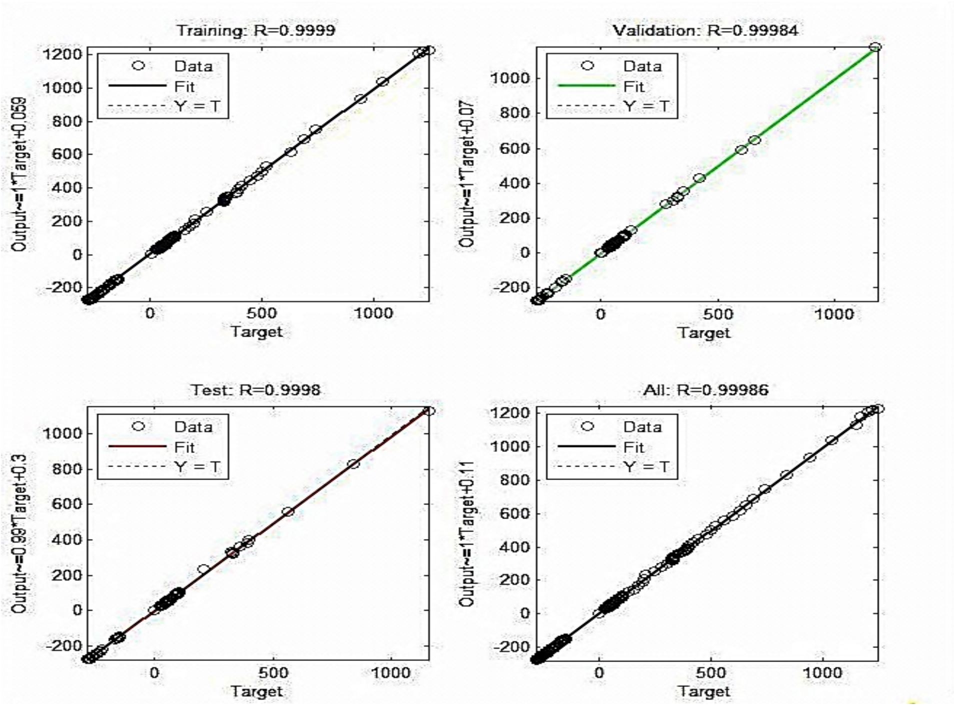

Fig. 7- Network performance in predicting the corrosion rate on corrosion 1:20:10:5 Education concretes.

to 1, suggesting successful performance and high convergence in the neural network. The obtained results from the simulation of the model for the corrosion rate are presented in Table 6 and Figure 8.

**Table 6**
Simulation results of corrosion rate for 3600 days using a simulation model.

| System | MS | Ferrogard901 | FA | Slag | Control |
|---|---|---|---|---|---|
| Corrosion rate (mpy) | 0.20 | 0.28 | 0.31 | 0.33 | 0.42 |

**Table 7**
Corrosion rate Variation for estimating the construction state [36]

| Corrosion Rate | Corrosion Probability (mpy) |
|---|---|
| Low | 0-0.04 |
| Moderate | 0.04-0.2 |
| High | 0.2-0.4 |
| Severe | >0.4 |

The mean of the corrosion rate for the mixture schemes simulated after 3600 days is presented in Figure 8. According to previous studies, the most reinforcement corrosion will happen after about 10 years of exposure in a marine environment, so the average of this time was selected for simulation. The corrosion rate results can be analyzed based on Table 7.

The corrosion rate of the first mixture (the control) is more than the other mixtures and clearly in the severe corrosion range (more than 0.4 mpy). In the mixtures with pozzolanic materials and inhibitor except MS concrete, the simulation shows the state of the structure lies in the high corrosion

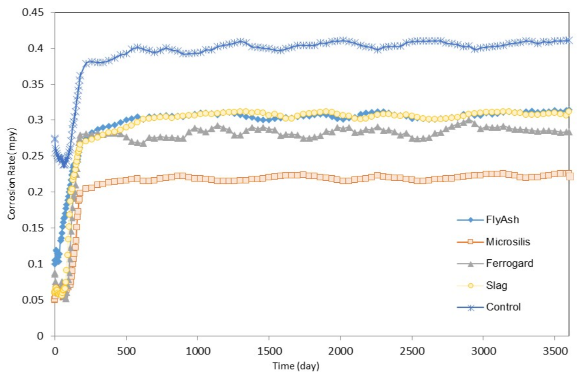

Fig. 8 - Predicted Corrosion Rate vs Time in the simulated model.

zone, and for the MS mixing design after 10 years, nearly experienced a slow corrosion condition which is mainly due to the decrease in the permeability of the chloride ion into the concrete [8, 29].

Due to the structure and size of the MS, it is used as a filler to decrease the porosity of concrete mixtures. As a result, the lower porosity leads to a reduction in the corrosion rate. Actually, it is obvious from figure 8 that the lowest corrosion rate and the best protection happens with the mixture with 10% MS as a pozzolanic material and the average corrosion rate in this mixture after 3600 days is 0.2 mpy, which is in the moderate corrosion range.

In the simulation and anticipation of the corrosion current density with a neural network, various times for the input layer and the corrosion

**Table 8**

Result of corrosion current density for 3600 days by simulation model

| System | MS | Ferrogard901 | FA | Slag | Control |
|---|---|---|---|---|---|
| Current density (μA/cm$^2$) | 0.38 | 0.62 | 0.71 | 0.77 | 0.96 |

Table 9

Result of corrosion potential for 3600 days by simulation model

| System | MS | Ferrogard901 | FA | Slag | Control |
|---|---|---|---|---|---|
| Potential of corrosion (mV) | -225 | -231 | -233 | -236 | -258 |

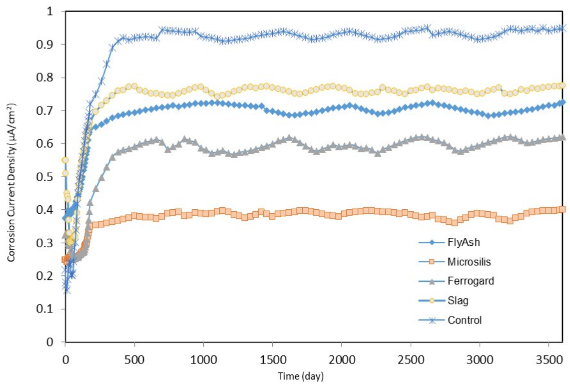


Fig. 9 - Predicted Corrosion Current Density vs Time in the simulated model.

current density of mixtures were selected as input layer parameters. The result of second simulation for corrosion current density is presented in Figure 9 and Table 8. As indicated in the curve of Figure 9, the reference concrete has the most corrosion current density. Among concretes with pozzolanic and inhibitor materials, the corrosion current density has been decreased significantly between them, the mixture with MS has the lowest corrosion current density, and it is in the low corrosion range. The calculations, which were carried out by Rodriguez to interpret corrosion current density, are presented in Table 5.

According to the presented results, it is obvious that the reinforcement corrosion in the control sample, concrete with Ferrogard 910, and pozzolanic materials except MS, are all in the high corrosion range. Although all of them have the high corrosion probability, but there is meaningful difference between them. The existence of pozzolanic materials in concrete decreases porosity, and, as a result, the permeability of the chloride ions is lower and decreases the destruction and corrosion current density. Moreover, using Ferrogard 901 as a corrosion inhibitor is an effective way to protect concrete reinforcement. It penetrates into the concrete and protects the reinforcing bars by forming a protective layer on the steel surface. In other words, the corrosion current density for concrete containing Ferrogard 901 is 0.62, which is closer to the low probability zone, and leads to more protection against reinforcement corrosion. The related corrosion current density for the control mixture is close to the very high corrosion probability, and has the least protection.

In another model, the corrosion potential of five mixtures were considered as an output parameter and time was the only input parameter. The results from the simulation of this model for the corrosion potential average of 3600 days are shown in Table 9 and Figure 10.

Figure 10 suggests that the reference concrete corrosion potential is less than for the other mixtures. Regarding the other investigations [34], if the corrosion potential as opposite to the saturated Calomel electrode stands between -130 to -280 mV, the corrosion is evaluated as moderate. Nevertheless, the concrete that belongs to the first mixture has less potential than the others. Thus, the corrosion possibility in this kind of concrete is more than for the other concrete, and conversely the value of the concrete corrosion potential of MS is more than for the other mixtures and stands in the high protection range. Therefore, this mixture follows the protection rule better than others have.

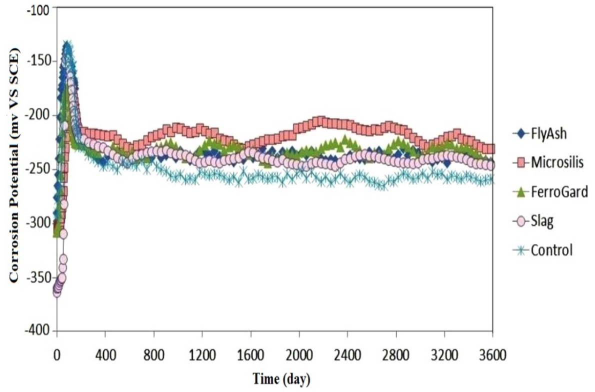


Fig. 10 - Predicted Corrosion Potential vs Time in the simulated model.

## 4. Conclusions

In the present study, different mixing designs to investigate the effect of pozzolanic materials and an inhibitor on the corrosive behavior of reinforced concrete at 180 days and simulated in this manner for 10 years, including MS, FA, and slag as pozzolans, and Ferrogard

901 as an inhibitor alongside control concrete, were utilized to evaluate concrete. All additives were used in the optimum percent introduced through other studies. MS, FA, slag, and Ferrogard 901 were used in the optimal percent of 10%, 25%, 25%, and 3% of cement weight. The simulation was carried out with ANNs and indeed the non-linear manner of rebar corrosion in concrete in the marine solution (3.5% NaCl) was simulated by the FFBP algorithm.

The predicted results from the ANNs affirm the outcomes of tests after 180 days. It can be concluded that adding 10% of MS has the most effect in reducing the corrosion rate and current density. For example, the results show that adding 10% of MS has decreased the corrosion rate and current density from 0.42 mpy and 0.96μA/cm2 in reference concrete to 0.20mpy and 0.38$\mu A/cm^2$ respectively, which is significantly lower than in other samples. Moreover, the corrosion potential was also anticipated by ANNs, and its results acknowledge previous experiments' conclusions. The corrosive potential of reference concrete after 3600 days reached -258 mv, while this number is -225 for a concrete mixture with 10% of MS. This is the highest corrosion potential and provides the best protection among other mixtures.

Although the mixtures with slag and FA behaved very similarly to each other and there is no significant different between their results, the predicted data indicate that after 10 years, concrete in the marine environment containing MS, Ferrogard901, FA, and slag will have the safest conditions, respectively. It is also worth mentioning that the results show that the corrosion rate and the corrosion current density will increase over time in all the samples. However, they become almost constant after a specific time, due to the formation of a passive layer around the reinforcement which protects it from chloride ions penetrating the surface of the rebar.

Comparing the results at 180 days and the predicted 3600 day test results explain that the minimum change in the corrosion rate and the corrosion current density has occurred in the mixtures that contain MS and Ferrogard 901, respectively. In addition, it is clear that the sample with 10% MS is the only mixture that remains in the low corrosion probability zone and the moderate corrosion rate after 3600 days. Finally, based on the presented results, and due to the effect of MS which decreases concrete mixture porosity, using 10% of MS as alternative to portland cement is strongly recommended to improve corrosion resistance in reinforced concrete.

**REFERENCES**

[1] Abosrra, L., A. F. Ashour, and M. Youseffi. "Corrosion of steel reinforcement in concrete of different compressive strengths." Construction and Building Materials 25.10, 2011, 3915-3925.

[2] Asrar, Nausha, et al. "Corrosion protection performance of microsilica added concretes in NaCl and seawater environments." Construction and Building Materials 13.4 1999, 213-219.

[3] Adhikary, Bimal Babu, and Hiroshi Mutsuyoshi. "Prediction of shear strength of steel fiber RC beams using neural networks." Construction and Building Materials 20.9, 2006, 801-811.

[4] Altun, Fatih, Özgür Kişi, and Kamil Aydin. "Predicting the compressive strength of steel fiber added lightweight concrete using neural network." Computational Materials Science 42.2 (2008): 259-265.

[5] Andrade, C., and C. Alonso. "Test methods for on-site corrosion rate measurement of steel reinforcement in concrete by means of the polarization resistance method." Materials and Structures 37.9 (2004): 623-643.

[6] Basma, Adnan A., Samer A. Barakat, and Salim Al-Oraimi. "Prediction of cement degree of hydration using artificial neural networks." ACI Materials Journal 96.2 (1999): 167-172.

[7] Chalee, W., Ca Jaturapitakkul, and P. Chindaprasirt. "Predicting the chloride penetration of fly ash concrete in seawater." Marine structures 22.3 (2009): 341-353.

[8] Dias, W. P. S., and S. P. Pooliyadda. "Neural networks for predicting properties of concretes with admixtures." Construction and Building Materials 15.7 (2001): 371-379.

[9] Elshafey, Ahmed A., Mahmoud R. Haddara, and H. Marzouk. "Damage detection in offshore structures using neural networks." Marine Structures 23.1 (2010): 131-145.

[10] Haddara, M. R., and C. Guedes Soares. "Wind loads on marine structures." Marine Structures 12.3 (1999): 199-209.

[11] Inan, G., et al. "Prediction of sulfate expansion of PC mortar using adaptive neuro-fuzzy methodology." Building and Environment 42.3, 2007, 1264-1269.

[12] Isaia, Geraldo C., Antonio Luiz Guerra GASTALDInl, and R. Moraes. "Physical and pozzolanic action of mineral additions on the mechanical strength of high-performance concrete." Cement and concrete composites 25.1 2003, 69-76.

[13] Jamil M, Zain MFM, Basri HB. Neural Network Simulator Model For Optimization in High Performance Concrete Mix Design. Eur J Scient Res 2009, 61-8.

[14] Karakurt C, Topçu İB. Effect of blended cements produced with natural zeolite and industrial by products on alkali-silica reaction and sulfate resistance of concrete. Constr Build Mater. 2011, 25, 1789-95.

[15] Lim, Chul-Hyun, Young-Soo Yoon, and Joong-Hoon Kim. "Genetic algorithm in mix proportioning of high-performance concrete." Cement and Concrete Research 34.3, 2004, 409-420.

[16] Leng, Faguang, Naiqian Feng, and Xinying Lu. "An experimental study on the properties of resistance to diffusion of chloride ions of fly ash and blast furnace slag concrete." Cement and Concrete Research 30.6, 2000, 989-992.

[17] Mouli, M., and H. Khelafi. "Performance characteristics of lightweight aggregate concrete containing natural pozzolan." Building and environment 43.1, 2008, 31-36.

[18] More, Anurag, and M. C. Deo. "Forecasting wind with neural networks." Marine structures 16.1, 2003, 35-49.

[19] Mukherjee A, Nag Biswas S. Artificial neural networks in prediction of mechanical behavior of concrete at high temperature. Nucl Eng Des. 1997; 178:1-11.

[20] Montemor, M. F., A. M. P. Simoes, and M. M. Salta. "Effect of fly ash on concrete reinforcement corrosion studied by EIS." Cement and Concrete Composites 22.3, 2000, 175-185.

[21] Millard, S. G., et al. "Environmental influences on linear polarisation corrosion rate measurement in reinforced concrete." NDT & E International 34.6, 2001, 409-417.

[22] Ni, Hong-Guang, and Ji-Zong Wang. "Prediction of compressive strength of concrete by neural networks." Cement and Concrete Research 30.8, 2000, 1245-1250.

[23] Oh J-w, Lee I-W, Kim J-T, Lee G-W. Application of Neural Network for Prediction of Concrete Mixes. ACI Mater J. 1999, 96:61-7.

[24] Parthiban, Thirumalai, et al. "Neural network analysis for corrosion of steel in concrete." Corrosion Science 47.7 2005, 1625-1642.

[25] Lopes, Tiago A. Piedras, and Nelson FF Ebecken. "In-time fatigue monitoring using neural networks." Marine structures 10.5 , 1997, 363-387.

[26] Rodriguez, P., E. Ramirez, and J. A. Gonzalez. "Methods for studying corrosion in reinforced concrete." Magazine of Concrete Research 46.167, 1994, 81-90.

[27] Al-Rabiah, A. R., and Roger Baggott. "Durability requirements for reinforced concrete construction in aggressive marine environments." Marine Structures 3.4 1990, 285-300.

[28] Reyes-Diaz, E. P., et al. "Corrosion Resistance of Lightweight Concrete Made of Ternary Mixtures." Sixth International Conference on Concrete under Severe Conditions: Environment and LoadingCentro de Investigacion y de Estudios Avanzados del IPN, Unidad MeridaConsejo Nacional de Ciencia y Tecnologia, CONACyTUniversidad Autonoma de YucatanGobierno del Estado de YucatanH Ayuntamiento de la Ciudad de MeridaH Ayuntamiento de la Ciudad de ProgresoAsociacion Latinoamericana de Control de Calidad, Patologia y Recuperacion de la Construccion, ALCONPAT MexicoCEMEX Concretos SA de CVWR GRACE Holdings SA de CVPENMAR SA de CVSIKA Mexicana SA de CVBASF Mexicana SA de CV. 2010.

[29] Shannag, M. J. "High strength concrete containing natural pozzolan and silica fume." Cement and concrete composites 22.6, 2000, 399-406.

[30] Topçu, İlker Bekir, Ahmet Raif Boğa, and Fatih Onur Hocaoğlu. "Modeling corrosion currents of reinforced concrete using ANN." *Automation in Construction* 18.2 2009, 145-152.

[31] Thomas, Michael DA, and Phil B. Bamforth. "Modelling chloride diffusion in concrete: effect of fly ash and slag." *Cement and Concrete Research* 29.4 ,1999, 487-495.

[32] Topçu İB, Sarıdemir M. Prediction of mechanical properties of recycled aggregate concretes
Containing silica fume using artificial neural networks and fuzzy logic. Comput Mater Sci. 2008,42:74-82.

[33] Ukrainczyk, Neven, Tomislav Matusinović, and Velimir Ukrainczyk. "Comparison of NEeutral Network Durability Models for Reinforced Concrete Structures." *10. Conference on Materials, Processes, Friction and Wear MATRIB'05*. 2005.

[34] Yeh, I-C. "Modeling of strength of high-performance concrete using artificial neural networks." *Cement and Concrete research* 28.12 (1998): 1797-1808.

[35] Yeaua KY, Kim EK. An experimental study on corrosion resistance of concrete with ground granulate blast-furnace slag. Cement Concrete Res. 2005;35:1391-9.

[36] Zaleski-Zamenhof, L. C., and B. C. Gerwick. "CONCRETE MARINE STRUCTURES-A STATE-OF-THE-ART REVIEW." ,1990.

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## MANIFESTĂRI ŞTIINŢIFICE / SCIENTIFIC EVENTS

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