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Prediction of bond strength between concrete and rebar under corrosion using ANN

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Abstract. Corrosion of the rebar embedded in concrete has a fundamental role in the determination of life and durability of the concrete structures. Researches have demonstrated that artificial neural networks (ANNs) can effectively predict issues such as expected damage in concrete structures in marine environment caused by chloride penetration, the potential of steel embedded in concrete under the influence of chloride, the corrosion of the steel embedded in concrete and corrosion current density in steel reinforced concrete. In this study, data from different kind of concrete under the influence of chloride ion, are analyzed using the neural network and it is concluded that this method is able to predict the bond strength between the concrete and the steel reinforcement in mentioned condition with high reliability.

Keywords: corrosion of steel; concrete; artificial neural networks; modelling; bond strength

1. Introduction

In recent decades, the corrosion of reinforced concrete has become worse because of the widespread use of de-icing salts on bridge decks and highways. According to the results of researches, every year million tons of road salts are used for deicing, anti-icing purposes. Despite the fact that concrete make a protective shield for reinforcing steel, corrosion is inevitable because salts (chlorides or sulfates) penetrate the concrete and reach the steel level. Since the corrosion products of the steel will expand up to seven times its original size, they cause pressure within the concrete which leads to cracking of concrete cover. Cover cracking expose the reinforcing bars to further corrosion. There have been many catastrophic collapses of structure made by corrosion of reinforcing steel resulting in injury and death, such as the collapse of the Berlin Congress Hall (Amleh 2000). Numerous studies have been carried out to model the steel corrosion and its effects on concrete (Liu and Weyers 1998, Böhm *et al*. 1998, Schmidt-Döhl and Rostásy 1999, Kranc and Sagüés 2001, Steffens *et al*. 2002). These models are consistent with the qualitative expectations of corrosion behavior in the system. However, long-term predictions using each of these models haven't been reported (Parthiban *et al*. 2005). So to predict and analyze the behavior of steel in concrete, corrosion modeling and predicting chloride profiles, numerical and analytical procedure is necessary. For this purpose, the neural network can be used for modeling and prediction. Artificial neural networks (ANNs) are interconnected networks of large numbers of computing neurons (or units) which has distributed parallel processing structure (Karray and De Silva 2004). Neural network consists of three layers, input layer, an intermediate (hidden) layer and output. Input layer neurons only have distributor role, while the hidden layer neurons have weight and play the role of the operating functions. Therefore, the input and output data are used to train the neural network so that the network has the ability to predict the results for the next input data.

For each network, the data are divided into training and test sets. Choose the appropriate number of training patterns is very important. There is no general rule to determine the size of the training data. A sufficient number of samples, displays certain features that is needed in the domain of education (Parthiban *et al*. 2005).

The ANN analysis was used to predict the compression strength of polypropylene fibre mixed concrete by Erdem *et al*. (2013). The efficiency of ANNs in predicting the shear strength of RC deep beams was investigated as a different approach to the strut-and-tie method by Yavuz (2016). Aktas and Sirac Ozerdem (2016) developed models to accurately predict the performance of fresh concrete subjected to vibration by ANN model. Keskin (2017) used an ANN model for predicting shear strength of SFRC slender beams without stirrups. Ongpeng *et al*. (2017) employed an ANN model to predict compressive stress in concrete using ultrasonic test results. Mancini *et al*. (2017) derived a reliability-based design bond strength relationship for tensed lapped joints and anchorages in reinforced concrete structures. Blomfors *et al*. (2019) used probabilistic methods to develop partial factors for application in an existing bond model, to assess the safety of corroded reinforced concrete structures.

In this paper, the application of ANNs in the field of

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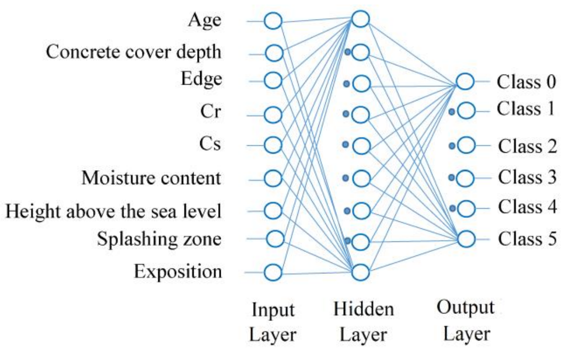

Fig. 1 Selected network structure (Ukrainczyk *et al*. 2004)

corrosion of steel in concrete is studied, according to the previous researches. ANN is also used to predict the bond strength between concrete and steel rebar reinforcement under corrosion. For this purpose, the data of 132 specimens of concrete (Amleh 2000) under the influence of chloride ion is used. These specimens are selected from corrosion phenomenon studies of the Dickson Bridge. The input layer of this model consists of four parameters such as concrete cover (mm), mass loss due to corrosion (%), width of longitudinal crack due to corrosion (mm) and chloride ion content at rebar level (%). The bond strength (MPa) between concrete and rebar is considered as single parameter of output layer of the ANN model. It should be noted that 84% of the data is used for network training and 16% of them is considered for testing and validation.

2. Application of ANNs in the field of corrosion of steel in concrete

By studying different researches that have done in the field of neural networks and the corrosion of steel in concrete, it is concluded that the application of neural networks categorized as following: Predicting expected damages in concrete structures in marine environment caused by chloride penetration (which causes steel corrosion in concrete); Predict potential of steel embedded in concrete under the influence of chloride (which causes steel corrosion in concrete); Modeling to predict the corrosion of steel embedded in concrete; Investigation on corrosion current density in steel reinforced concrete.

2.1 Predict the expected damage in concrete structures in marine environment caused by chloride penetration

In 2004, Ukrainczyk *et al*., showed that neural network is a useful tool for classifying damage and prediction of the level of damage that can be expected due to chloride penetration and corrosion of steel in concrete structures in marine environment. Their model has 9 inputs and 6 outputs classified based on the type of damage (Ukrainczyk *et al*. 2004), Fig. 1. Inputs are: Age (years); Cover depth (cm); Rebar level Cl^-, *Cr* (%); Surface Cl^-, *Cs* (%); Moisture content, *w*, vol. (%); Height above sea, *h* (m); Rebar in edge, *Edge*; Splashing zone; Exposure.

They demonstrated that the developed ANN model can predict damage level accurately.

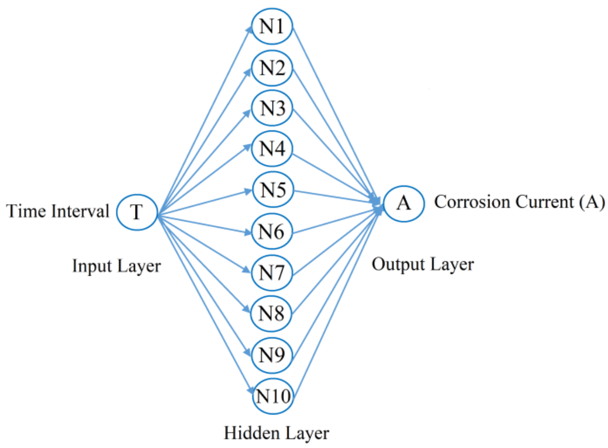

Fig. 2 System used in neural network model for the first simulation (Topçu *et al*. 2009)

2.2 Predicting potential of steel embedded in concrete under the influence of chloride

In 2005, Parthiban *et al*., by using different sets of data for training and testing a neural network with an input layer, a hidden layer and an output layer, predicted the potential of steel embedded in the concrete slab under the influence and without the influence of chloride. To do this, the potential of steel in different parts of each slab was measured by the electric potential generated between the steel reinforcement and base copper electrode. In all cases, the potential of the embedded rebars obtained at 36 various considerable points in each slab in specified distances. The data obtained and saved in a data file. The obtained data for each slab averaged for analysis with ANNs. The ANN analysis successfully predicted the experimental results (Parthiban *et al*. 2005).

2.3 Modeling and predicting the corrosion of steel embedded in concrete

In 2009, Tupcu *et al*., modeled corrosion of steel embedded in concrete by using neural networks. To do this, various samples with different types of cement with and without fly ash created and the corrosion of the steel embedded in concrete using the effective voltage test was investigated. For this reason, two different simulations were performed for corrosion currents, hidden layer of both of them consist of 10 neurons. The first purpose of the simulation was modeling the nonlinear behavior of corrosion processes in time for any kind of concrete (Topçu *et al*. 2009), Fig. 2.

Prediction of corrosion behavior by taking specific samples be considered as the second study. In this case, as in the first simulation, the corrosion is defined as output, Fig 4. Therefore, in the second simulation all the corrosion currents combined into single data set, and an ANN consists of fly ash, the type of cement, curing time and time interval

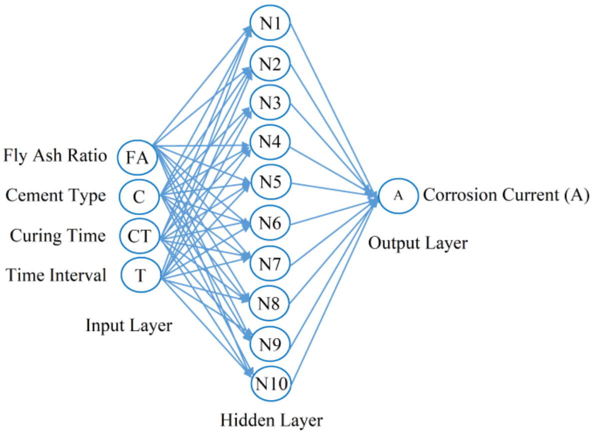

Fig. 3 The second system used in neural network model for simulation (Topçu *et al*. 2009)

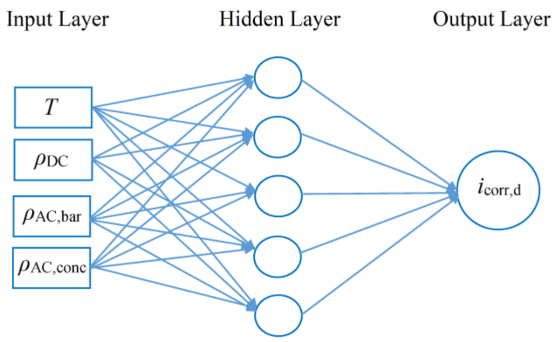

Fig. 4 The architecture of multilayer perceptron neural network (Sadowski 2013)

as Input constructed and tested (Topçu *et al*. 2009). Here, as the first simulation, the corrosion is defined as output, Fig. 3.

It concluded that the neural network generates predictive values close to the experimental measured values.

2.4. Investigation of corrosion current density in steel reinforced concrete

In 2013, Sadowski used the ANNs to assess the steel corrosion rate in concrete without a direct connection to the reinforcement. The multilayer perceptron neural network architecture used for this examination is illustrated in Fig. 4. The ANN generalized by one input layer, one hidden layer with five neurons and one output layer. The parameters considered in the study are: air temperature (T), AC resistivity over the steel bar ($\rho_{AC,bar}$), AC resistivity remote from the steel bar ($\rho_{AC,conc}$), DC resistivity over the steel bar (ρ_{DC}), and corrosion current density (i_{corr}). The study showed that it is able to predict the corrosion current density by ANNs, especially via the multilayer perceptron neural network (Sadowski 2013).

3. Case study, modeling and data processing

In 2000, Amleh studied the various mixtures of concrete in the pullout testing program, with four various thicknesses of concrete cover (25, 50, 75 and 100 mm) to investigate the bond deterioration of rebar in concrete due to corrosion. The nomenclature of specimens derived as follows (Amleh, 2000):

- The first letter and the second numeral state the type of concrete mixture applied in the specimen as follows:
  - C1: Point Tupper (fly ash w/scm=0.32)
  - C2: Thunder Bay (fly ash w/scm=0.32)
  - C3: Sundance (fly ash w/scm=0.32)
  - C4: Normal portland cement (w/c=0.32)
  - C5: Normal portland cement (w/c=0.42)
  - C6: High aluminum cement (w/c=0.37)
- The third number state the specimen number.
- The fourth letter state the specimen size according to concrete cover:
  - *A*=100 mm
  - *B*=75 mm
  - *C*=50 mm
  - *D*=25 mm

In Almeh2000 study, bar diameter, the anchorage length and the steel strength were kept constant in order to limit the extent of the research. The following numbers were selected for the pullout test: Bar diameter=19.5 (No. 20 bar); Embedded length=280 mm and Length of specimen=305 mm (Amleh 2000).

In this study, to predict the bond strength between the concrete and steel rebar reinforcement, data of 132 concrete specimens (Amleh 2000) under the chloride ion penetration (which causes steel corrosion in concrete) is analyzed using ANN. Since ANN needs less formal statistical training and it can absolutely detect intricate non-linear relationships, it is used for modeling in the present research. By iterative regulation, ANN has the ability to detect possible interplay between predictors and target variable where multiple various training algorithms can be adopted for a robust derivation of the specifications within the predictor data (Tu 1996, Ravinesh *et al*. 2017). Properties of data in present study is given in Table 1. For example, data for some specimens (20 concrete specimens selected from top and

Table 1 Properties of data in this study

	Concrete Cover (mm)	Mass loss due to corrosion (%)	Width of longitudinal crack due to corrosion (mm)	Chloride ion content at rebar level (%)	Bond Strength (MPa)
Average	61.74	7.53	1.27	0.32	5.59
Max	100	28.48	6	1.87	12.89
Min	25	0.13	0	0.01	0.24
Standard deviation	27.43	5.953	1.363	0.37	2.86

Table 2 Data of 20 concrete specimens under the chloride ion penetration (Amleh 2000)

Specimen	Concrete Cover (mm)	Mass loss due to corrosion (%)	Width of longitudinal crack due to corrosion (mm)	Chloride ion content at rebar level (%)	Bond Strength (MPa)
C1-5A	100	8.91	3	1.08	6.53
C1-6A	100	5.76	0.4	0.14	7.89
C1-7A	100	4.9	0.2	0.12	8
C1-8A	100	6	0.5	0.15	7.68
C1-3B	75	5.4	1.2	0.44	6.55
C1-4B	75	3	0.2	0.05	7.22
C1-5B	75	2.2	0.1	0.03	7.54
C1-6B	75	1.2	0	0.02	10.89
C1-7B	75	4.5	0.4	0.1	7.04
C1-8B	75	5	0.8	0.12	6.9
C6-3C	50	7.2	1.8	0.43	5.12
C6-5C	50	10.48	2	0.55	4.48
C6-6C	50	2.98	0.8	0.29	6.31
C6-8C	50	6.97	1.4	0.4	5.12
C6-3D	25	11.53	3	0.84	0.9
C6-4D	25	8.2	2	0.28	2.05
C6-5D	25	0.63	0	0.01	4.67
C6-6D	25	12.23	4	1.87	0.81
C6-7D	25	5.5	0.8	0.17	3.06
C6-8D	25	3.9	0.6	0.03	3.77

bottom of the total set) is given in the Table 2.

multilayer perceptron (MLP) (Öztaş *et al*. 2006) is a kind of feed-forward networks, in which the information spread among the network neurons just in the forward direction (Karray and De Silva 2004). In present study, MLP neural network is used. A program in MATLAB using neural network Toolbox (Demuth and Beale 2002) is prepared and used with 132 data set which are the concrete specimens under the penetration of chloride ions. 84% of the data is used to train the neural network system and 16% of them is considered for test and validation. Considered neural network model includes four input, concrete cover (mm), mass loss due to corrosion (%), width of longitudinal crack due to corrosion (mm) and chloride ion content at rebar level (%); one hidden layer with five neurons and one output layer (bond strength between the concrete and steel reinforcement bars (MPa)). The scheme of the neural network is depicted in Fig. 5.

The network is trained by using Marquardt-Levenberg algorithm (Karray and De Silva, 2004). Since this algorithm gives extremely quick convergence with lower root mean square error (RMSE) (Topçu *et al*. 2009), it is considered in present research. The number of epoch, performance (MSE) value, gradient decent value and Mu are 21 iterations, 0.691, 1.08 and 0.001 respectively. A neural network training state with 3-layer is shown in Fig. 6. The training stops when the validation parameter max_fail reached maximum 0 validation checks at epoch 21 with the gradient decent value 1.0849 with reasonable Mu value 0.001 which would cause the convergence of the network fast. It is expected that too small Mu value cause the network to converge slowly.

Fig. 7 illustrates the performance of neural network training. It indicates that network training has no any

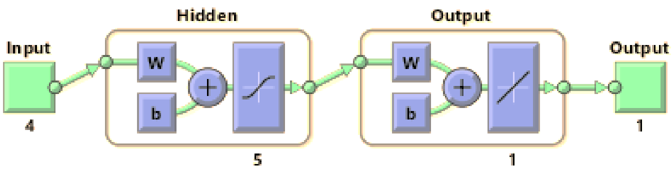

Fig. 5 Neural network scheme

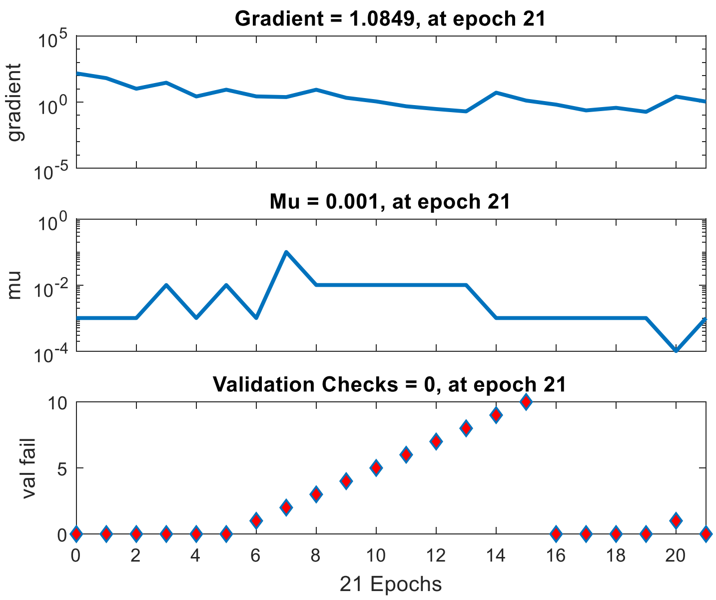

Fig. 6 ANN training state for five hidden neurons

considerable problem. The best validation performance obtained at epoch 21 with the value of 1.2233.

The regression analysis in ANN model is performed. It is carried out as statistical tool to evaluate that how the output and target value of the network match (Salit *et al*. 2015). Regression function requires targets and outputs values and draw the linear Regression of targets according to the outputs (Mohammadhassani *et al*. 2013). Training, test, validation and over all regression are shown in Fig. 8. The data in the model are represented by small circles. After

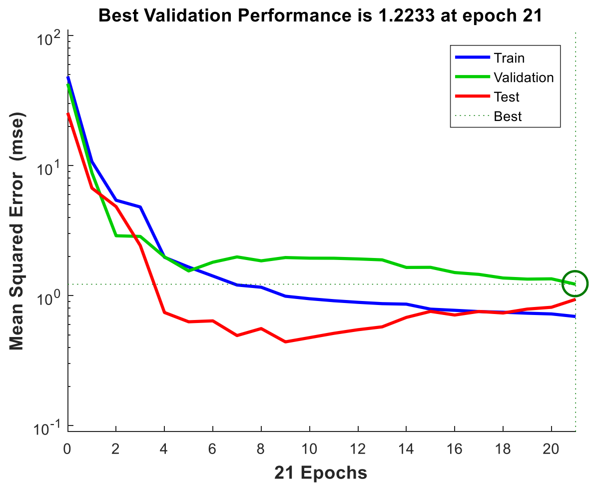

Fig. 7 Performance of Network training

plotting the regression diagram, it is necessary to investigate the model to validate the fitness. Regression coefficient (*R*) that represents the fitness of data points on a line or curve is useful parameter in determination of fitness. The best fit is found to be a straight line. The dashed line represents the outputs equal to targets. The *R* value for every network procedure indicate the relationship between the outputs and the targets. Exact linear relationship between outputs and targets is obtained at *R*=1. In this model, the network exhibits significantly acceptable *R* values near to one. The training *R*, validation *R*, test *R* and over all *R* values are equal to 0.95781, 0.84217, 0.95884 and 0.95294 respectively. This demonstrates that the model and the network procedure of training, testing and validation are acceptable. Note that the horizontal axis of the regression curves represents objective or measure of bond strength between concrete and rebar steel reinforcement by MPa (N/mm^2) and the vertical axis represents the bond strength predicted by the network.

The error histogram displays the data point where they fit noticeably worse as compared to the majority of data (Fig. 9). It is understood from the histogram that most errors happen between -0.6878 and 0.5683.

To demonstrate the accuracy of the ANN model, outputs of trained network (predicted bond strength) for concrete specimens are compared with experimental results (measured bond strength), Fig. 10.

As can be seen, predicted results from the network are in

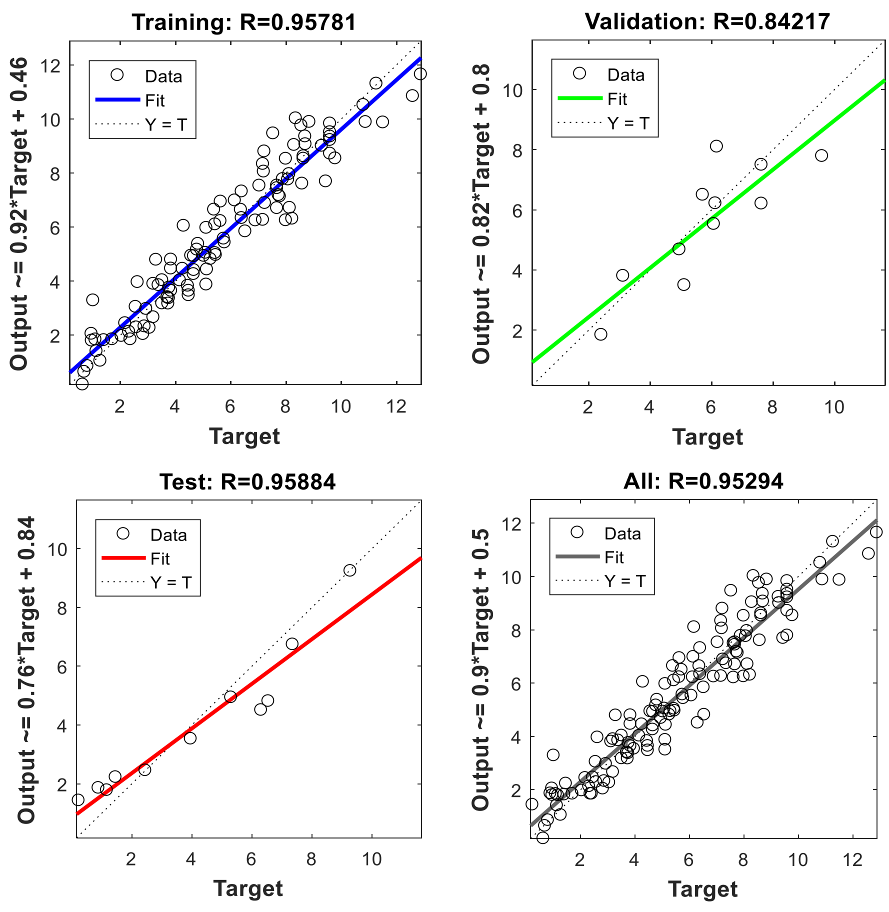

Fig. 8 Regression of network

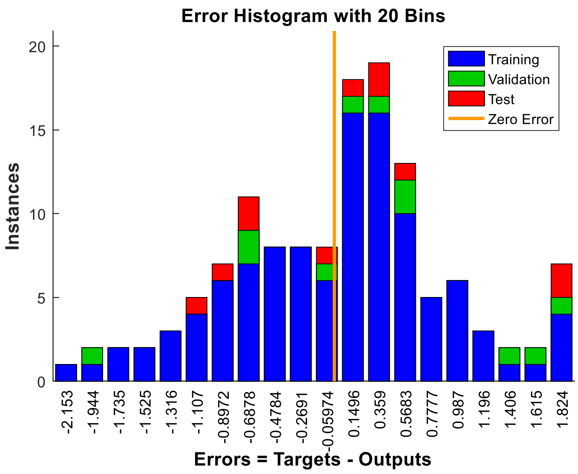

Fig. 9 Error histogram generated after ANN modeling

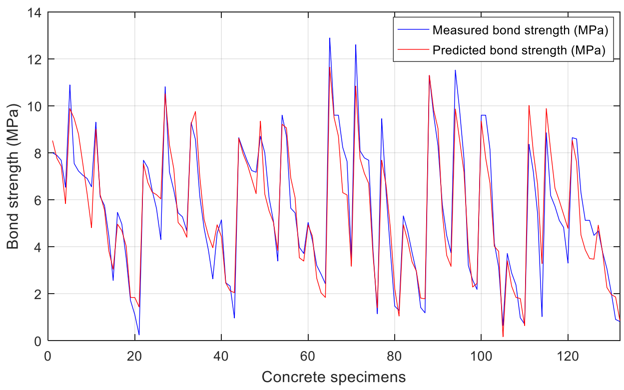

Fig. 10 Comparison of predicted bond strength of network and measured values for concrete specimens

very good agreement with experimental results, in some specimens match exactly on them which demonstrate the efficacy of the predictive network.

4. Conclusions

Artificial neural networks (ANNs) can be used as a powerful tool that is capable of modeling and predicting the behavior of steel corrosion in concrete and their effective factors. As it can be seen, regression diagrams and also performance evaluation result implies excellent regression coefficient of test data. Negligible difference between network performance evaluation diagram for training and testing data as well as proper network convergence imply that the predicted acceptable bond strength by network. By comparing predicted and measured bond strength for concrete specimens, it is observed that experimental results are very close to predicted results by ANN. So we can say that the neural network is capable of predicting the bond strength between the concrete and steel reinforcement bars in the concrete specimens under the influence of chloride corrosion process with high reliability, and therefore ANNs can be used to predict the results of experiments on other specimens. By this means experimental costs reduced greatly. If the input parameters of this study can be measured from laboratory samples of concrete structures exposed to corrosion, the results of the neural network prediction in this study can be used especially in the following areas:

• Assessment of concrete structures damaged because of corrosion of the reinforcing steel
• The reliability-based design of new concrete structures for durability against corrosion of the reinforcement
• Repair and rehabilitation of existing corrosion-damaged concrete structures
• To develop a reliability-based method for design for durability against corrosion for service life prediction of new and existing concrete structures.

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