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BOND STRENGTH PREDICTION MODEL OF CORRODED REINFORCEMENT IN CONCRETE USING NEURAL NETWORK

*Nolan C. Concha[1] and Andres Winston C. Oreta[2]

[1]De La Salle University, Philippines; [2]Faculty, De La Salle University, Philippines

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ABSTRACT: The expansion of corrosion products in the steel-concrete interface offers radial tensile stress resulting in the development of cracks in reinforced concrete structures. This corrosion-induced crack promotes bond reduction involving intricate non-linear interactions. To deeply understand the underlying mechanisms in the bond strength of corroded rebars in concrete, a novel bond prediction model using artificial neural network (ANN) was developed. Accelerated corrosion was performed to 108 cube samples using 500 $\mu A/cm^2$ current density. Steel bond strength after 35 and 70 days impressed corrosion exposure of concrete cube samples was measured using a single pull out test. The compressive strength, tensile strength, rebar diameter, embedment length, concrete cover, ultrasonic pulse velocity (UPV), crack severity, and corrosion level were the predictors in the ANN bond model. Among all the bond strength models considered in this study, the proposed neural network model provided the most desirable bond estimates in good agreement with experimental results. The ANN model further showed superior prediction performance against the derived regression model.

Keywords: Bond strength, Corrosion, Crack severity, Impressed current

1. INTRODUCTION

Corrosion of steel reinforcements due to chloride ingress is regarded as one vital structural health concerns in concrete structures. Embedded bars at this rusting stage expand and develop radial stresses in concrete resulting to cracking, bulging, and spalling of concrete. Corrosion also results to the buckling, snapping, and ineffective bond characteristics of reinforcements due to continued reduction in the effective bar size. When subjected to reinforcement corrosion, concrete structures experience delamination in which the oxidized metal requires greater space causing a wedge-like stress. Surface and internal cracks tend to develop in concrete and promote exposure of reinforcements to corrosion. This, in turn, imparts an excessive reduction in the bond strength characterized by the adhesion and slippage resistance between steel and the enveloping concrete. Ultimately the serviceability and durability of reinforced concrete are significantly reduced and potentially results in structural collapse. Because of this, studies in developing bond strength and corrosion resistance of reinforcing bars has remained a popular research interest [1].

In the development of corrosion models particularly in the numerical and analytical modelling, several ideal assumptions were considered. The study of El Maaddawy and Soudki [2] assumed that the thickness of corrosion around the bar was uniformly distributed and exerts a constant radial pressure in the enveloping concrete. The actual underlying bond behavior of steel bars in concrete might not be adequately described by these assumptions since actual corrosion formations in steel bars vary along the rebar-concrete interface. In fact, there have been observed contradicting results obtained between analytical and empirical equations due to the uniform thick-walled cylinder analogy adopted in the development of the models [3]–[4]. The formation of corrosion and its corresponding effect on the bond between concrete and steel involves complex interactions. Concrete strengths, rebar diameter, and embedment length are among the important variables affecting the corrosion development. One potential method to model the dominant and complicated interrelationships among the variables of corrosion and bond is artificial neural networks (ANNs). Recent researchers have found the power of ANN to model complex interactions and provide superior prediction performance [5]–[8]. Through the set of input-output data from a battery of tests conducted, ANN develops a network of neurons that can be tuned up to synthesize information and eventually learn.

A novel prediction model of the bond behavior of reinforcing steel bars in reinforced concrete due to corrosion using artificial neural network will be developed in this paper. Bond strength model using multiple regression will be derived as well for further comparison. A larger number of variables will be considered in the modeling including crack and continuity of concrete. The model will allow early detection of the level of bond degradation between concrete and steel in a simple and fast approach. This, in turn, leads to timely repair that can improve the safety and prolong the service life of the structure.

2. BOND STRENGTH MODELS OF CORRODED STEEL BARS IN REINFORCED CONCRETE

Impressed corrosion method was used by most researchers in the development of bond-corrosion model. The effects of corrosion level in bond strength loss and cracking of concrete using impressed method were investigated by previous studies [9]–[11]. Monotonic pull out test was conducted on concrete samples to develop bond strength models. Derived models showed reasonable agreement between the measured experimental results and empirically estimated values of bond strength. Unlike any other studies that focus on bond strength, the study of Yaciner [1] model an equation for the ultimate bond strength (τ_{bu}) using multiple linear regression. The bond equation is dependent on concrete compressive strength (f'c), cover (c) to bar diameter (D) ratio and corrosion level (C_L). Results showed that an increase in concrete compressive strength and concrete cover improved the measured bond strength. Moreover, it was found out that an increase in the compressive strength with constant concrete protective cover resulted in higher bond strength than a constant compressive strength with increasing concrete protective cover. Using ultra-high toughness cementitious composite, Hou et al. [12] developed a model to estimate the bond strength (τ_u) of a corroded rebar as a function of rebar diameter (d), bond length l_b, and corrosion ratio (ρ_c). The bond decreased up to 15% corrosion ratio but is almost the same with non-corroded samples. The prediction equation was able to give acceptable results as compared with experimental values recorded in the conduct of pull out tests of cylindrical samples. Table 1 shows the summary of bond prediction models from various literature.

Table 1 Bond strength models of rebars in concrete

Cabrera	$f_{bo} = 23.478 - 1.313C$
Lee and Weyers	$\tau_{\max} = 0.34\sigma_b - 1.93 \text{ if } \Delta_w < \Delta_{wc}$ $\tau_{\max} = 5.21e^{-0.0561\Delta w} \text{ if } \Delta_w \geq \Delta_{wc}$
Chung et al.	$u_b = 16.87 \text{ for } C_o \leq 2.0$ $u_b = 24.7C_o^{-0.55} \text{ for } C_o > 2.0$
Yalciner et al.	$\tau_{bu} = 0.40551 f'c - 0.25306\left(c/D\right) + 0.97926 C_L \left(R^2 = 0.98\right)$
Hou et al.	$\tau_u = 0.335\left[-0.124\rho_c^2 + 1.183\rho_c + 93.504\right]\left(\dfrac{d}{l_b}\right)^{0.379}$

3. EXPERIMENTAL PROGRAM

3.1 Materials and Specimens

The experiment in this study used 108 concrete cube samples in total with side length 200 mm. Bar diameters, concrete cover (cc) and embedment lengths (L_d) were varied in the concrete cube samples. Three deformed reinforcing bars of 16mm, 20mm, and 25mm in diameters with a corresponding concrete cover of 60mm, 70mm, and 80mm were used. Embedment lengths of 50mm, 75mm, and 100mm were used to achieve an even bond stress distribution within the entire embedment length of the rebar. The properties of the materials were tested in compliance with ASTM standards. The density and water absorption of coarse aggregates were measured and found to be 1572.028 kg/m3 and 0.402% respectively. Similarly, for fine aggregates, the recorded values of 1533.801 kg/m3, 3.2 %, and 2.673 for density, water absorption, and fineness were respectively observed. These results were used to proportion three design mixes having target compressive strengths of 21 MPa, 28 MPa, and 35 MPa. Table 2 shows the material proportions and average strengths corresponding to each mixture using 0.68, 0.57, and 0.47 preliminary ratios of water-cement, slump values from 25mm to 100mm, and 2% entrapped air.

Table 2 Concrete design proportions and strengths

Design Mix	W kg/m^3	C kg/m^3	CA kg/m^3	FA kg/m^3	f'c (MPa)	ft (MPa)
1	189	301	1018	866	22	2.08
2	189	359	1018	806	29	2.61
3	190	436	1018	726	36	3.14

3.2 Testing of Specimens

After curing for 28 days to gain strength, the samples were immediately immersed in a 5% brine solution as shown in fig. 1. A current density (i) of 500 $\mu A/cm^2$ from a constant power source was allowed to pass through the reinforcements embedded in the concrete prism to accelerate the corrosion. A total of 108 samples were subjected to accelerated corrosion for 35 days and 70 days to generate sufficient corrosion products that will develop internal radial stress enough to cause internal and external cracks in the concrete.

Fig. 1   Concrete cubes under accelerated corrosion

Likewise, the crack severity (CS) expressed as the product of the crack length (L) and the representative crack width (W) was determined. In order to measure the opening of crack in each of the samples, several polycarbonate reference points were attached to the surface of the concrete. The development of the distance between the reference points was measured using an electronic caliper. Using the measured values in every crack line, the product of the length and width was taken and the sum of all the results in each specimen was used to represent the crack severity of the sample. After which ultrasonic pulse velocity test was performed to assess the quality of concrete samples after 35 days and 70 days impressed current. The transducer and receiver of the UPV apparatus were positioned in direct set up. The results of the test were used as an input variable in the bond model representing the homogeneity and compactness of concrete.

The bond strength of the rebar in concrete after accelerated corrosion was measured using pull out test in compliance with ASTM C234-91a. The pull-out strength was determined by measuring the maximum force required to pull the rebar from the concrete sample. The bond strength (μ) was calculated by taking the ratio of the maximum applied force (P) and the surface area of the reinforcing steel rebar in contact with concrete. Figure 2 shows the fractured concrete sample after performing a single pull out test using the universal testing machine.

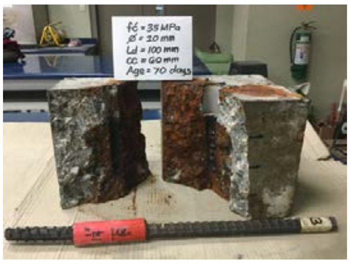

Fig. 2 Concrete cube sample after pull out test

Prior to the casting of concrete in the mold, deformed bars were weighed to determine the initial mass (Mo) before accelerated corrosion. After performing the accelerated corrosion process and pull out testing of the samples, all pulled off bars were cleaned from corrosion products at the surface of the rebar and weighed to record the final mass (M_f). The actual percentage of mass loss or corrosion level (C_L) of each bar was calculated using eq. (1).

$$C_L = \frac{M_o - M_f}{M_o} x100\% \tag{1}$$

4. EXPERIMENTAL RESULTS

4.1 Experimental Data Statistics

Among the 108 cube samples subjected to impressed current method of accelerated corrosion, 74 of which or 69% were able to exhibit crack formations due to the level of corrosion in the reinforcement. There were observed significant changes in the recorded values between uncracked and cracked groups. A sudden drop in the UPV and bond strengths were obtained from almost all the samples in the group. The average UPV of 4081 km/s and average bond strength of 6.591 MPa for cracked samples were substantially lower than the mean values from the uncracked samples. These reductions were attributed to the excessive amount of corrosion in the reinforcement resulting in the development of internal and surface cracks in the samples. Moreover, the corrosion level was even higher for samples in the cracked group with an average and maximum values of 1.015% and 3.254% respectively. Samples having high corrosion levels, in general, correspond to high crack severity. The maximum observed crack severity was 215.492 mm^2 and the average value in all the samples was 77.791mm^2. The dominant compressive strength in the cracked group was 29 MPa while the diameter of the rebar was 25mm. Based on the standard deviation and COV, higher variability was observed for UPV, corrosion level, crack severity, and bond strength of the samples.

4.2 Bond Strength Regression Model of Corroded Reinforcement

The bond strength as a function of concrete compressive strength, tensile strength, embedment length, diameter, concrete cover, UPV, crack severity, and mass loss was developed using multiple linear regression. The derived polynomial regression equation with an adjusted R square of 0.899 and standard error of 3.262 is given in eq. (2). The embedment length, rebar diameter, the root of the product of compressive strength and tensile strength of concrete, and the crack severity offered a reduction in bond strength as described by the negative coefficients in the model. For the other variables, however, a direct correlation with the bond strength was observed. Among the variables considered in the model having P values less than 0.05, the embedment length, rebar diameter, UPV, and crack severity offered a significant effect on the bond strength. The observation was reasonable since these parameters were interrelated and dominated the behavior of bond. A substantial change was observed in the experimental bond values particularly on the vast number of samples in the cracked group attributed to the variation of these parameters.

$$\tau = -0.106 l_d - 0.236d + 0.009cc - 0.064\sqrt{f'c*ft} + 0.006UPV - 0.040C_S + 0.840\mathrm{C}_L \tag{2}$$

The performance of the regression model in predicting bond resistance of concrete is shown in fig. 3. A vast majority of points lied closely to the 45° line indicating satisfactory prediction performance of the model. The Pearson correlation coefficient of the scatter plot was 0.831 showing good agreement between experimental and predicted bond values. The average prediction error was 31.81% with a minimum error of 0.61%. In all the predicted bond strengths, roughly 45% lied within ±20% error while 19% of the predictions provided more than ±50% error. Considering the fuzziness of the experimental bond strengths, the bond regression model was able to provide a satisfactory prediction of the bond strength of concrete.

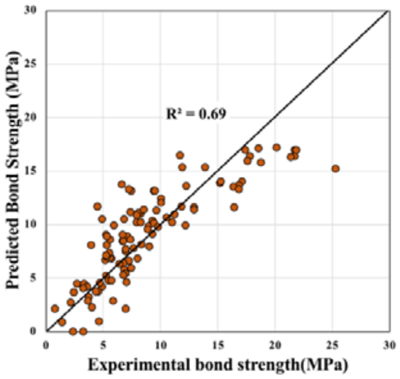

Fig. 3 Bond strength regression model predictions

5. NEURAL NETWORK MODELLING

5.1 Framework of the Neural Network Model

The input layer of the neural network model was composed of eight individual distinct nodes. Each node represents the predictors in the model which includes the compressive strength (f'c), tensile strength (ft), embedment length (l_d), rebar diameter (ϕ), concrete cover (cc), ultrasonic pulse velocity (UPV), corrosion level (C_L), and crack severity of concrete (C_s). One hidden layer was used in the model and the number of hidden nodes was varied between 5 to 8. The output layer was composed of one node representing the bond strength output of the model. Neural network model structure having 8 input nodes, 4 hidden layer neurons, and a single node in the output layer was denoted as N 8-4-1. In the development of the model, the learning algorithm used was feedforward backpropagation algorithm. The hyperbolic tangent sigmoid function $f(n)=2/(1+e-2n)^{-1}$ was employed as neural activation function which returns values between -1 to 1 in the output layer. An error tolerance of 0.001 and maximum cycles of 100000 were used as threshold criteria to cease the simulation process. Early stopping, validation phase in the development of the model, and a few numbers of hidden nodes were considered to minimize the chance of overfitting and enhance the generalization of the ANN model.

5.2 ANN Model Experimental Data and Simulations

The bond strength results obtained from short-term pull out test of 100 samples was used in the development of the model. Seventy percent of the data pairs were used in the training phase of the model and the other 30 percent was used in the testing phase. Carpenter and Barthelemy [13] suggested a minimum number of training data pairs not greater than the number of weights and biases to achieve distinct approximation. Further, an overdetermined data of 20-50% will yield satisfactory performance of the ANN model [14]. Considering the neural network architecture N 8-7-1 having seven nodes in the hidden layer and using 20% overdetermined network, the required minimum number of input-output data pairs must be between 76 to 96. With this constraint, the data used in the simulation was found sufficient to achieve the desired performance of the various ANN models. In selecting the best performing ANN architecture among the variations considered, mean squared error (MSE) and correlation coefficient (R) were used as performance metrics. The model having the least MSE and closest R-value to 1.0 will emerge as the best ANN model. The result of simulations of four ANN models with their corresponding MSE and R are shown in table 3. Apparently, the neural network model having 7 nodes in the hidden layer provided the most desirable performance indicators. N 8-7-1 model exhibited the least bond strength prediction errors in good agreement with experimental values. The model was able to achieve learning considering multiple predictors and fuzziness in the introduced data pairs. The MSE and R of the derived model were 2.678 and 0.957 respectively. In contrast, N 8-5-1 model having 5 neurons was the least performing model.

Table 3 Variation of ANN models

Model	Number of hidden nodes	Performance criteria	
		MSE	R
N 8-5-1	5	3.623	0.941
N 8-6-1	6	3.478	0.943
N 8-7-1	7	2.678	0.957
N 8-8-1	8	3.148	0.952

5.3 Connection Weights and Biases of N 8-7-1 Model

Table 4 shows the weights and biases of the proposed neural network model. Each seven nodes in the hidden layer were associated with connection weights in the input and output layers. The relative importance of each predictor in the model using the causal inference procedure developed by Garson [15] was also reflected in the table. The ultrasonic pulse velocity was found to be the most significant predictor in the bond strength with a relative importance of 20.11%. Associated with this variable were the crack severity and corrosion level having a relative importance of 13.01% and 15.63% respectively. The results were reasonable since higher corrosion levels offer immense radial tensile stress in the samples resulting in excessive crack formations and sudden fall in the UPV values. Measured bond strengths in the pull-out test were significantly affected by the change in values of these three independent variables. The concrete compressive strength was found to be the least significant predictor having 8.08% relative importance. The strength of concrete barely offered a substantial effect on the measured bond strength of the samples. Majority of the samples achieved internal and external crack formations.

Table 4 Connection weights and biases of N 8-7-1 model

Hidden Nodes	Input Layer								Output Layer
	f'c	ft	L_d	ϕ	cc	UPV	Cs	C_L	
1	1.7118	1.1845	-0.6978	-0.0326	-1.0295	5.3538	-0.2653	-2.4959	0.2793
2	0.4372	0.5614	-1.4098	0.2691	-3.4692	-0.2920	2.4862	0.7990	0.0155
3	-0.4544	1.1419	1.3558	0.3752	0.2338	2.9630	-3.0908	3.2125	2.8476
4	2.4621	1.0616	3.1235	4.2368	0.5334	-1.7865	1.3760	1.3494	-0.2731
5	-0.1467	1.5563	0.8980	0.7151	0.5034	1.8726	0.3141	-0.4767	0.9385
6	0.0887	0.8101	1.4231	0.3394	0.2469	2.5854	-2.4950	2.5881	-3.0964
7	-2.2206	-1.6088	1.4915	-3.1291	-1.3239	1.0983	0.3039	2.1818	0.3688
Biases	-5.1069	-0.6449	2.8476	-0.1126	3.8667	-0.0931	-3.8237		-0.7184
Rel. Impt. (%)	8.09	10.618	12.66	10.03	9.85	20.11	13.01	15.63	

5.4 Prediction Performance of N 6-6-1 Model

About 76% and 84% from training and test datasets respectively were within the ±10% error. Though there were few misfits of roughly 15% providing more than 25% prediction errors, the model was able to perform well in training and testing phases of the simulation. The experimental and predicted values of the model for both phases were plotted as shown in fig. 4. The model was able to perform better in the testing phase giving an R-value of 0.983 and an average error of 16.27%. The R-value and average error in the training phase of the model were 0.954 and 19.69% respectively. A vast majority of samples with an overall R equal to 0.957 exhibited a close fit from the 45° line showing desirable agreement between predicted and experimental results. The average ratio of experimental to predicted values of 1.03 further demonstrates robust performance of N 8-7-1 model in the prediction of bond strength.

5.5 Comparison Between N 8-7-1 Model and Other Bond Strength Models

Various bond prediction models available in the literature were considered and compared to the performance of the proposed N 8-7-1 model. Eight bond strength values from experimental data were not used in the calibration. This dataset was used to test the bond performance of the proposed ANN model against the developed models of Yalciner et al. [1], Cabrera [9], Lee et al. [10], Chung et al. [11], Hou et al. [12], and the developed regression equation. The experimental and predicted results of the enumerated models were plotted in fig. 5. The scatter plot diagram was so dispersed demonstrating large deviations of the points from the 45° line. The models developed by Cabrera [9], Chung et al. [11], and Hou et al. [12] gave overestimated values of the bond strength due to the limitations of the variables considered. Most of the proposed models provided significant errors in the prediction results. This can be attributed to the inability of the models to capture significant bond reduction in the presence of internal and surface cracks in the concrete. The proposed N 8-7-1 model, on the other hand, was able to exhibit robustness in predicting the bond strength of the samples. A close fit can be seen from the graph with R-value of 0.971. The limitation of the hidden nodes and the early stopping adopted in the development of the model worked so well to improve the generalization. The average observed error in the prediction results was 19.53% with maximum and minimum errors of 45.48% and 3.68% respectively. The superiority of the proposed model was credited to equally important variables such as UPV and crack severity which was not considered in other models.

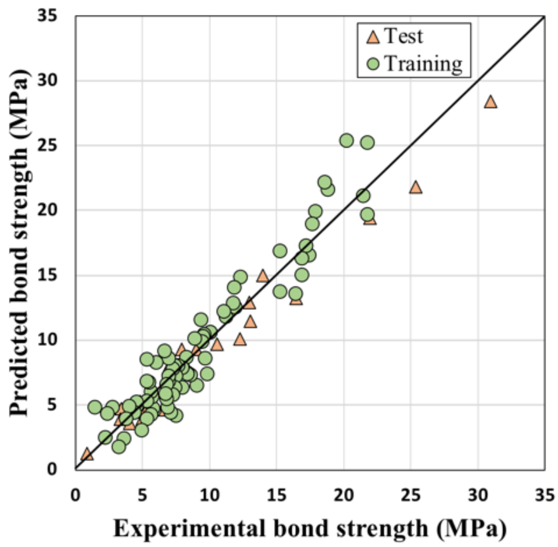

Fig. 4 Bond strength regression model predictions

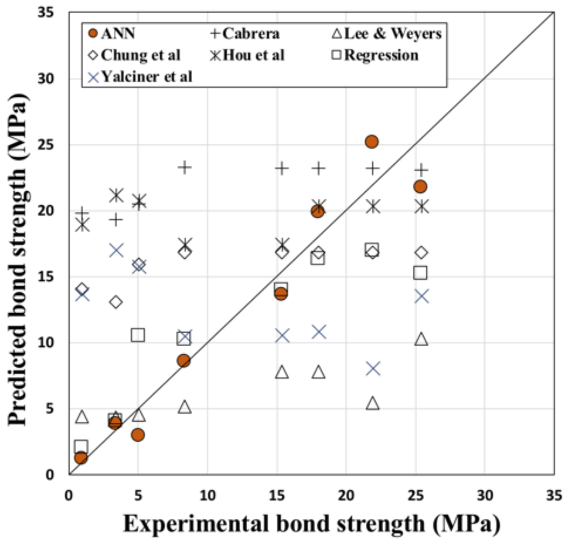

Fig. 5 Bond predictions using different models

6. CONCLUSIONS

In the simulation of several neural network architectures having eight input predictors and one response variable, the N 8-7-1 model with seven nodes in the hidden layer emerged as the best performing model. The proposed model provided mean squared error and Pearson correlation coefficient of 2.678 and 0.957 respectively indicating robustness in estimating the pull-out resistance of corroded reinforcements in concrete. The model further demonstrated superior prediction performance and generalization among the bond models considered in this study. Crack severity and ultrasonic pulse velocity predictors of the model in relation to the formation of corrosion products in rebars offered significant effects in the bond behavior. The emergence of these two predictors was in agreement with the results of causal inference procedure providing respective high relative importance of 20.11% and 13.01%. With all the desirable attributes of the model, the proposed N 8-7-1 can be used to conveniently estimated the bond resistance of corroded steel in reinforced concrete.

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