

AN IMPROVED PREDICTION MODEL FOR BOND STRENGTH OF DEFORMED BARS IN RC USING UPV TEST AND ARTIFICIAL NEURAL NETWORK

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ABSTRACT: The composite action of reinforcement in the surrounding concrete involve a complex and non-linear mechanism. Inadequate understanding of the underlying interactions may lead to designs with insufficient amount of bond resistance of reinforcing bars in concrete structures. To investigate the effects of various parameters on the bond strength of steel bars in concrete, 54 cube samples with varying embedded reinforcements and strengths were prepared. The samples were cured for 28 days and tested using ultrasonic pulse velocity (UPV) test for sample homogeneity and single pull out test for bond strength. Data gathered in the experiment were used in the development of bond strength model as a function of compressive strength, concrete cover to rebar diameter ratio, embedment length, and UPV using artificial neural network (ANN). Of all the bond strength models considered from various literatures, the neural network model provided the most satisfactory prediction results in good agreement with the bond strength values obtained from the experiment. The UPV parameter was found to be one of the most significant predictors in the neural network model having a relative importance of 20.57%. This suggest that the robust prediction performance of the bond model was attributed to this essential component of the model. The proposed model of this study can be used as baseline information and rapid non-destructive assessment for zone wise strengthening in reinforced concrete.

Keywords: Bond strength; Artificial neural network; Ultrasonic pulse velocity; Parametric analysis

1. INTRODUCTION

One of the essential components that must be achieved for structural design is the bond strength of the steel reinforcement to the enveloping concrete. The resistance of the rebar against slipping from embedment due to pulling force is defined as bond strength. The composite action between steel and the enveloping concrete may be destroyed by the inadequate bond resistance and may result to concrete brittle failure [1]. The bond does not only ensure the composite action but also controls structural behavior of the reinforced concrete. There are numerous number of researches embarking on bond behavior of steel bars in concrete are available in the literature. Results recorded from experiments of these studies were used to develop analytical and empirical models. Due to the complex non-linear relationships that exist in the rebar and concrete, several ideal assumptions were adopted to simplify the systems involved in the development of the models. These estimates however insufficiently represent the existing underlying mechanism of bond strength in reinforced concrete. As a result, the derived bond equations provided estimates that are in good agreement only within the framework of their study. It is therefore indispensable to consider other modelling techniques that are powerful enough to

generally adopt with the complex behavior of bond strength in reinforced concrete.

A convenient and precise way to model the complex interactions in such intricate systems is by means of artificial neural network [2-6]. There is no need to consider ideal assumptions to simplify the modelling approach as the neural network process raw data from actual experiments. Through the aid of a set of input-output data, a system of interconnected neurons can be developed that is capable of predicting variables from a certain set of inputs. In this work, novel prediction model of bond resistance of reinforcing rebars in reinforced concrete using neural network will be developed. A greater number of variables will be considered in the modeling including concrete compressive strength, tensile capacity of concrete, homogeneity of concrete using ultrasonic pulse velocity, rebar diameter, embedment length and concrete cover. The performance of the model will be compared to other available bond strength models in the literature. Multiple regression model will also be derived for comparison.

2. BOND STRENGTH MODELS

The bond strength of reinforced concrete members depends on many different variables such as compressive strength, rebar size, length of

embedment, type of loading (dynamic or static), development length, and bar spacing. The use of pull out test played a vital role in the development of bond strength model. In the study of Hadi [7], 14 simple pull out tests were performed in measuring the bond strength of 500 MPa grade steel embedded in a 70 MPa concrete compressive strength. Different bar diameters from 12 mm to 36 mm were used having concrete cover of 120 mm and 150 mm. The derived model using regression analysis is given in eqn 2. The equation is dependent on the compressive strength of concrete (f'_c), concrete cover (c), diameter of the rebar (d_b), and the length of embedment (L_d). The bond strength equation was compared with other established models and comparison showed that among the models considered, the proposed model provided the best prediction values in agreement with the experimental results.

$$u = 0.08305\sqrt{f'_c} \left(22.8 - 0.208 \frac{c}{d_b} - 38.212 \frac{d_b}{L_d} \right) \quad (1)$$

Unlike any other studies that focus on bond strength, the study of Yalciner et al [8] made use of multiple linear regression in order to model an equation for the ultimate bond strength (τ_{bu}) that is dependent to compressive strength (f'_c) of concrete and the cover (c) to bar diameter (D) ratio. An increase in concrete compressive strength and concrete cover would also result to an increase in bond strength. Moreover, it was found out that an increase in the compressive strength with constant concrete protective cover resulted to higher bond strength than a constant compressive strength with increasing the concrete protective cover. Using multiple linear regression, the following equations with high correlation coefficient values were established:

$$\tau_{bu} = -2.7143 + 0.3621f'_c + 2.3296 \left(\frac{c}{D} \right) \left(R^2 = 0.96 \right) \quad (2)$$

A larger number of variables were considered in the study of Diab et al [9] on bond performance and ultimate design of bond stress of normal and high strength concrete. Samples having different compressive strength (f_{cu}), concrete cover (c), size of the bar (d_b), length of embedment (L_d), rib height (h_r), and rib spacing (s_r) were tested using single and double pull out tests. The bond stress equation of samples having compressive strength of 80 MPa was developed using multiple regression as shown in eqn 3. The reliability of this equation was validated using values recorded from experiments and compared with forecasted values provided by other available models.

$$\tau_{pr} = \sqrt{f_{cu}} \left[0.08262 + 0.09234 \left(\frac{c}{d_b} \right) + 1.6038 \left(\frac{d_b}{L_d} \right) + 0.6318 \left(\frac{h_r}{s_r} \right) \right] \quad (3)$$

There is a satisfactory agreement of the proposed equation as described by the average value of actual to predicted bond strength ratio of 0.89.

In most of the studies enumerated for bond strength models, other equally important factors were not considered such as tensile strength and homogeneity of concrete. Thus, the results of the studies do not provide a substantial and complete discussion of the composite action between steel and concrete. Further, the derived models can only be applied to specific cases of bond strength to which the models were calibrated. In most of the studies involving non-linear relationships of multiple variables like bond stress, several ideal assumptions were usually adopted to reduce the complexity of the system in the modeling process. In order to avoid these simplifications that may reduce the reliability of results, a more powerful modelling approach such as artificial neural network must be used.

3. EXPERIMENTAL PROGRAM

3.1 Materials and Specimens

In designing the correct proportion of concrete, raw materials need to exhibit desirable properties to ensure beneficial effect to the design mixture. With the advent of available standard testing procedures and duly accepted gaging criteria, this study was able to measure the physical properties of the materials used and found to be in good conditions for the production of concrete. Water used in the mix was in good quality and free from contaminants. The density and water absorption of the coarse aggregates used were 1572.028 kg/m³ and 0.402% respectively. These values were measured in accordance with ASTM C127-04. Using ASTM C127-04a and ASTM C136, the density, water absorption, and fineness of fine aggregates were respectively measured to be 1533.801 kg/m³, 3.2 %, and 2.673. Three distinct designs of concrete mixtures were prepared based on target compressive strengths of 21 MPa, 28 MPa, and 35 MPa. Using a slump interval between 25mm and 100mm, 2% entrapped air, and estimated water cement ratios of 0.68, 0.57, and 0.47, three design mixes shown in table 1 were obtained. A total of 54 cube samples having side length of 200 mm with embedded reinforcement were prepared for the conduct of pull out test. Variation in rebar diameter (16mm, 20mm, and 25mm), concrete cover (60mm, 70mm, and 80mm), and embedment length (50mm, 75mm, and 100mm) were used in this study.

Table 1 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

Immediately after molding and finishing, cube and cylindrical specimens were cured by immersing the samples in water for 28 days (ASTM C31). The dimensions of the cylindrical samples were 6 inches in diameter and 12 inches in height. After the specified age of curing period have been reached, the cylindrical samples were tested in three trials for compressive strength (ASTM C39) and tensile strength (ASTM C496) of concrete using the universal testing machine. To assess the quality of concrete, ultrasonic pulse velocity test was carried out to all the cube samples (ASTM C597). All lateral faces of the specimen were applied with liquid coupling material for better contact between the coupler and surface of the sample. The transducer and receiver of the UPV apparatus was placed in direct set up. Lastly, standard single pull out test (ASTM C234-91A) was conducted in all the concrete cube samples to measure the maximum force necessary to pull the rebar from the concrete as shown in fig.1. Bond strength between the rebar and enveloping concrete was obtained by taking the ratio of the stress load and the surface area of steel bar which is in contact with the concrete.



Fig. 1 Concrete cube sample under pull out test

4. EXPERIMENTAL RESULTS

Experimental Data Statistics

The statistics of 54 samples tested for ultrasonic pulse velocity and pull out tests were determined. The statistical description includes the mean, standard deviation, sample variance, maximum value, and minimum value of the geometric attributes and measured strengths of the samples. The maximum pulse velocity was 4537 km/s while

the minimum velocity was 4009 km/s. These values were measured from samples having 36 MPa and 22 MPa compressive strengths respectively. The observed values were reasonable since higher compressive strengths imply more solid or compact internal structure of the sample. The signal generated by the UPV apparatus travels faster in solid medium thus providing larger values of pulse velocity. The UPV standard deviation of 128.56 km/sec suggests that the measured UPV values of the samples were roughly close to the average UPV value of 4355 km/sec. Less variability in the measured values were also observed as describe by a relatively small COV of only 3%. In the bond strength however, a larger dispersion in the measured values were observed as indicated by large SD of 6.376 MPa and COV of 46.7%.

5. NEURAL NETWORK MODELLING

5.1 Framework of the Neural Network Model

The bond strength model was a function of 6 independent variables namely compressive strength (f_c), tensile strength (ft), embedment length (ld), rebar diameter (ϕ), concrete cover (cc), and ultrasonic pulse velocity (UPV). These variables were individually represented by 6 distinct nodes in the input layer of the neural network. To develop a simple ANN model, only one hidden layer was used with varying number of hidden nodes between 3 to 6. A single node in the output layer represents the bond stress in the model. Neural network architecture having 6 input nodes, 2 hidden layer neurons, and 1 output node was represented as N 6-2-1. Four ANN structures were developed having different number of nodes in the intermediate layer. The variation in the nodes was carried out to explore a better neural network topology. Feedforward backpropagation algorithm was used as the learning algorithm in the derivation of the models with hyperbolic tangent sigmoid function $f(n)=2/(1+e^{-2n})^{-1}$ as the neural activation function. This transfer function calculates a layer output that returns value between -1 to 1. Threshold criteria of 100000 cycles or an error tolerance value of 0.001 were used to terminate the simulation process. A few number of nodes in the hidden layer was considered to avoid overfitting in the development of the model. Early stopping in the testing phase was also carried out to further improve the generalization of the model.

5.2 ANN Model Experimental Data and Simulations

The least number of training data pairs that will provide unique approximation must not be less than the number of weights and biases associated with the neural network model [10]. Carpenter and

Hoffman [11] further suggest that 20-50% overdetermined ANN model tends to provide satisfactory prediction performance. The bond strength model in this study involved six predictors, one hidden layer, and one output node. This neural network structure (N 6-5-1) with five nodes in the hidden layer and using 20% overdetermined network required a minimum number of input-output data pairs between 42 to 50 [12].

The correlation coefficient (R) and the mean squared error (MSE) were used as performance metrics in selecting the best bond strength model. The best neural network structure among the variations considered will have the least MSE and the closest R value to 1.0. As shown in table 2 were the results of MSE and R of the four distinct ANN model architectures having different number of nodes in the hidden layer. It is evident that N 6-6-1 model provided the best performance among all the models considered in the simulation. After all the data in the output layer were transformed in their corresponding physical attributes, the errors can be calculated by subtracting the experimental values from the estimated values provided by each model. The measured errors in the predicted values of N 6-6-1 model were the least errors relative to the other neural network architectures inasmuch as the model obtained the least MSE of 1.491. Further, a better agreement between the experimental and predicted values of N 6-6-1 model was expected owing to its high Pearson correlation coefficient R equal to 0.981. Having these desirable results, the developed model successfully learned from the simulation given a limited number of experimental data.

Table 2 Variation of ANN models

Model	Number of hidden nodes	Performance criteria	
		MSE	R
N 6-3-1	3	5.247	0.938
N 6-4-1	4	3.413	0.957
N 6-5-1	5	2.287	0.972
N 6-6-1	6	1.491	0.981

5.3 Connection Weights and Biases of N 6-6-1 Model

After a series of simulations of different ANN architectures, the N 6-6-1 model emerged as the best performing architecture. The model has six normalized nodes in the input layer representing compressive strength of concrete (f'c), tensile strength of concrete (ft), embedment length (Ld), rebar diameter (ϕ), concrete cover (cc), and ultrasonic pulse velocity (UPV). The weights and biases of this network model upon simulation were shown in table 3. Using the causal inference procedure developed by Garson [13], the relative importance of each parameter was also reflected in the table. Apparently, the rebar diameter was the most significant predictor in the model having a relative importance of 29.29% followed by compressive strength (16.78%), and concrete cover (16.63%). This was reasonable since the bond strength in reinforced concrete is largely influenced by the change of these three parameters. The least significant predictor on the other hand was the UPV having a relative importance of only 8.32%.

Table 3 Connection weights and biases of N 6-6-1 model

Hidden Nodes	Input Layer						Output Layer
	f'c	ft	Ld	ϕ	cc	UPV	
1	1.2359	0.97265	-3.488	-0.7465	0.8836	0.7632	0.8562
2	-1.5151	-1.3295	-2.7982	0.01032	-0.69229	0.10122	-0.2242
3	0.25005	-0.3640	3.1946	2.3349	-0.99424	0.28041	-0.3132
4	-3.1719	-1.4096	1.0701	-2.4758	0.62345	-4.111	-0.6295
5	-1.8764	-1.253	0.74373	-2.1176	-0.6216	-0.6828	0.7191
6	-0.0100	-0.8921	-0.3019	-0.3384	-0.9233	0.5979	-0.3561
Biases	-5.4397	2.5168	-1.1038	-3.5886	-1.9855	-1.7898	0.12035
Rel. Impt.	16.78	13.43	15.15	29.29	16.63	8.32	

5.4 Prediction Performance of N 6-6-1 Model

Fig. 2 shows the comparison of the N 6-6-1 model predictions to the experimental values for both training and test data. The results obtained in both data sets were significantly correlated as described by their respective Pearson's correlation coefficients of 0.99 and 0.90. A vast majority of the plotted points

almost lied on the perfect line with an average prediction error of 6.86%. Roughly 90% of the predicted values of the model lied within the 10% error. Maximum and minimum errors of 64% and 0.01% respectively were observed in the estimated values. An average ratio between the experimental and predicted values of 0.998 was further obtained. This result suggests that the estimated bond strength

was very close to the measured bond strength. Based on these desirable results, the derived ANN model exhibited a robust prediction performance

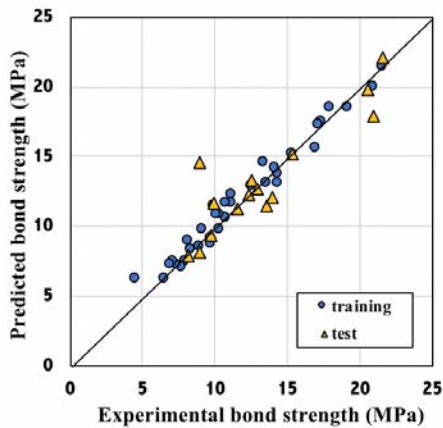


Fig. 2 ANN model predictions of bond strength

5.5 Comparison Between N 6-6-1 Model and Other Bond Strength Models

The performance of N 6-6-1 model was compared with other existing models developed by Hadi [7], Yalciner et al [8], Diab et al [9], and the developed model using multiple linear regression. Data sets in each study were consolidated and used to test the prediction performance of each bond strength model. Fig. 3 shows the plotted points of the experimental data against predicted values provided by the aforementioned models. A 45° line, also called the perfect line, was drawn in the figure to clearly observe the fitness of the models in estimating the bond strength of a given set of input parameters. The better the prediction, the closer will be the point to the perfect line. The scatter plot diagram displayed large dispersion of collected data sets from different studies. The figure suggests that, in general, the models performed satisfactory only within the set of data in which the models were respectively calibrated. Most of the models provided significant deviations from the perfect line for values beyond the framework of their study. These undesirable attributes showed poor generalization of the models considered. It may be because of the ideal assumptions made in the modelling process that may not be the actual underlying behavior of the interactions involved in the system. The model developed by Yalciner [8] exhibited the largest recorded average error of 75%. While the model developed by Diab [9] included the largest number of parameters, the average prediction error was 49%. In fact, Hadi's [7] model involving four independent variables offered better approximations providing a mean error of only 48% in the predictions. This observation implies that the superiority of the model does not rely on the number of variables involved in the modelling process but

by how significant is the contribution of each variable in the model. Looking closely on the plots of the proposed N 6-6-1 model, majority of the points showed relatively small deviations from the perfect line and obtained a correlation coefficient of 0.855. Among all the models considered in this study, the proposed ANN model gave the least average prediction error of only 29%. The maximum and minimum correlation coefficients were 0.855 and 0.062 respectively. About 72% of the consolidated data sets from various studies considered were captured by the ANN model with an error within $\pm 20\%$.

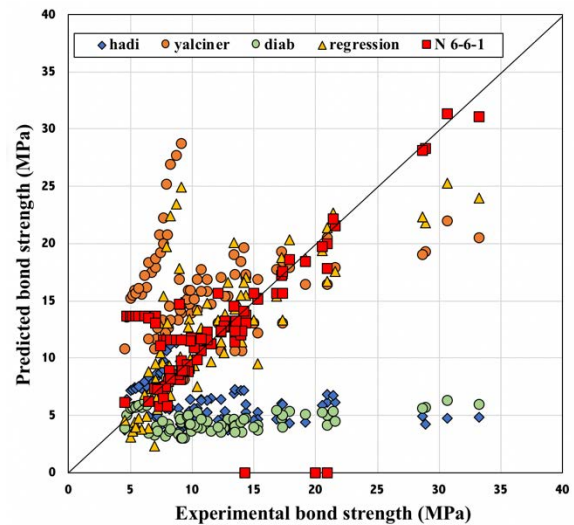


Fig. 3. Bond predictions using different models

6. CONCLUSIONS

Upon training various neural network architectures, N 6-6-1 model was found to be the best performing architecture having six input nodes, one hidden layer with five nodes, and one output node. The model was able to provide satisfactory prediction results capturing 72% of the data from experiments conducted and from various literatures with an error of at most 20%. Model comparison further showed that the proposed N 6-6-1 model provided the best prediction performance against other existing models considered in this study. The superiority was achieved since no simplified ideal assumptions were considered and only experimental results were used in the simulation process. This shows the power of artificial neural network in modelling highly complicated interactions using a limited source of experimental data.

The compressive and tensile strengths of concrete, concrete protective cover, and ultrasonic pulse velocity offered direct correlation with the bond strength behavior of reinforced concrete. The bond stress however decreases as the rebar diameter

and embedment length of reinforcement increases. This observation was attributed by the lateral contraction of the rebar due to Poisson's ratio. The derived model can be considered as rapid and convenient approach to estimate the bond strength of concrete. The results of the model can be used as baseline information in the design of reinforced concrete structures and other engineering applications involving bond strength.

7. REFERENCES

- [1] Rao GA, Pandurangan K, Sultana F, Eligehausen R. Studies on the pull-out strength of ribbed bars in high-strength concrete. In Proc. of FraMCoS-6 2007 (pp. 295-301).
- [2] Concha NC. Rheological Optimization of Self Compacting Concrete with Sodium Lignosulfate Based Accelerant Using Hybrid Neural Network-Genetic Algorithm. In Materials Science Forum 2016 (Vol. 866, pp. 9-13). Trans Tech Publications.
- [3] Concha NC, Oreta AW. Bond Strength Prediction Model of Corroded Reinforcement in Concrete Using Neural Network. International Journal Of Geomate. 2019 Feb 1;16(54):55-61.
- [4] Concha N, Oreta AW. A model for time-to-cracking of concrete due to chloride induced corrosion using artificial neural network. In IOP Conference Series: Materials Science and Engineering 2018 Oct (Vol. 431, No. 7, p. 072009). IOP Publishing.
- [5] Rinchon JP, Concha NC, Calilung MG. Reinforced concrete ultimate bond strength model using hybrid neural network-genetic algorithm. In 2017 IEEE 9th International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment and Management (HNICEM) 2017 Dec 1 (pp. 1-6). IEEE.
- [6] Concha NC, Dadios EP. Optimization of the rheological properties of self-compacting concrete using neural network and genetic algorithm. In 2015 International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment and Management (HNICEM) 2015 Dec 9 (pp. 1-6). IEEE.
- [7] Hadi MN. Bond of high strength concrete with high strength reinforcing steel. 2008. vol. 2, pp. 143-147
- [8] Yalciner H, Eren O, Sensoy S. An experimental study on the bond strength between reinforcement bars and concrete as a function of concrete cover, strength and corrosion level. Cement and Concrete Research. 2012 May 1;42(5):643-55.
- [9] Diab AM, Elyamany HE, Hussein MA, Al Ashy HM. Bond behavior and assessment of design ultimate bond stress of normal and high strength concrete. Alexandria Engineering Journal. 2014 Jun 1;53(2):355-71.
- [10] Carpenter, W. C., and Barthelemy, J., Common misconceptions about neural networks as approximators, *J. Comput. Civ. Eng.*, 1994, 83, 345 – 358.
- [11] Carpenter, W. C., and Hoffman, M. E., Training backprop neural networks, *AI Expert*, March 1995, 30–33.
- [12] Oreta AW, Kawashima K. Neural network modeling of confined compressive strength and strain of circular concrete columns. *Journal of Structural Engineering*. 2003 Apr;129(4):554-61.
- [13] Garson, G. D., Interpreting neural-network connection weights, *AI expert*, 1991,6(4), 46-51.

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