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A Computational Approach to Predict the Bond Strength of Thin Steel Rebars in Concrete by Means of Artificial Neural Networks

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Abstract. The bonding between steel rebars and concrete is one of the critical aspects of reinforced concrete structures. As a phenomenon influenced by many variables, it is challenging to establish how the steel-concrete adhesion can be described in the standards used for reinforced concrete design. This study used an experimental data set of 190 pull-out specimens to develop an artificial neural network (ANN). The data used in the modeling were collected from 8 different studies and were arranged as four input parameters: bar surface, bar diameter (ϕ), concrete compressive strength (fc) and the anchorage length (Ld). The output result was the pull-out load. Several scientific studies on this property have been performed since the 1940s, among many other investigations in this field. Generally, these studies refer to bars with diameters greater than 12.0 mm. However, few studies have evaluated the performance of reinforcing bars with diameters smaller than 10.0 mm, which includes 6.0-, 6.3-, 8.0- and 9.5-mm diameters, usually used in reinforced concrete elements. This work uses ANN to analyze and build a prediction model for the steel-concrete bond and its potential to deal with experimental data. The root mean squared error (RMSE) found for the maximum pull-out load in the pull-out test was 2.35 kN and the obtained R-squared was 0.94. Therefore, the pull-out load results found were compared with the results obtained through the equation available in CEB 2010. Finally, it is possible to conclude that the current model can satisfactorily predict the bond strength of thin bars.

Keywords: Steel-concrete bond; Thin rebars; Artificial neural network.

Introduction

Steel-concrete bonds are essential for the structural behavior of reinforced concrete structures and an extensive range of parameters influences the characteristics of the steel-concrete interface [1]. Many authors have conducted experimental investigations into the most critical influence parameters upon the bond, and the bonding characteristics are usually affected by the bar diameter, the anchorage length of bars, the concrete compressive strength, and the bar surface [2]. As a phenomenon influenced by many variables, it is a challenge to establish how steel-concrete adhesion can be described in standards used for reinforced concrete design [3].

Several scientific studies on this property have been performed since the 1940s [4,5], among many other studies in this field. Generally, these studies refer to bars with diameters greater than 12.0 mm [6,7]. However, few researchers have evaluated the performance of reinforcing bars with diameters smaller than 10.0 mm, which includes 5.0, 6.3, and 8.0 mm diameters, generally used in reinforced concrete elements [8].

One of the most used tests to evaluate the steel-concrete bond is the pull-out test, as described in RILEM-CEB RC [9]. The pull-out test consists of extracting a steel bar placed in the center of a cubic concrete specimen, as shown in Fig. 1. The bond strength can be calculated with the pulling load measured at one end and the displacement is measured at the other end, as shown in Eq. (1):

$$\tau = \frac{P}{\pi \cdot \phi \cdot L_d} \tag{1}$$

where τ is the bond strength, P is the applied load, ϕ is the rebar diameter and L_d is the anchorage length.

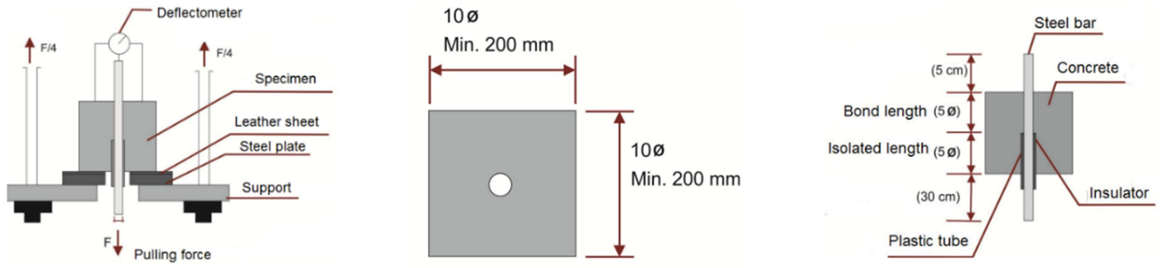

Fig. 1: Pull-out test set-up [9]

Equation (1) can be used to calculate the pull-out stress obtained from the experimental test, using the applied pull-out force, the bar diameter, and the bar anchoring length. However, this stress can only be obtained experimentally by destructive testing of the specimen. Despite the existence of analytical expressions for predicting the bond stress in the normative codes, these expressions only take into account the concrete compressive strength. One can also say that due to the great nonlinearity associated with the problem, it has been difficult to develop an analytical expression that takes into consideration all the variables used in the models [10].

The size effect of rebars in the bond has been illustrated direct or indirectly by some researchers. Some of them discussed the theme of size effect on the steel-concrete bond, including bar diameter and the anchored length on the pull-out test. The small number of scientific studies on the bond of thin bars cast doubts on the parameters used to calculate the anchorage length of these bars in reinforced concrete elements [3].

Technological advancement usually allows engineering problems to be solved with machine learning, and its applications are good examples of fields explored with different expectations and realistic results. In general, artificial intelligence systems have shown their ability to solve real-life problems, particularly in nonlinear tasks [11].

Structural engineering has been a field of significant development through the implementation and testing of new computational models, predicting the different properties of concrete mixtures. In the case of behavioral models, pattern recognition is relevant and computational intelligence methods can be used. Bio-inspired models can also be an excellent aid to the design of structures for civil engineering [12,13]. The steel-concrete bond has also been an object of study using artificial intelligence in several works, but usually with a rebar diameter greater than 10 mm [10,14].

Other works have presented similar studies to those presented in this paper involving computational methods that attempted to predict pull-out strength using smaller databases containing 89 pull-out tests performed by Carvalho [3]. These papers presented studies that used computational methods such as Support Vector Machine and Artificial Neural Network [15,16]. To improve the understanding of the pull-out phenomenon of steel bars in concrete blocks, this study similarly presents the use of a larger database, containing 190 specimens, obtained from several different studies [3,17–23]. The implementation of the model presented in this paper is similar to that used previously, however, an adjustment in the parameters used was necessary to achieve better results. Furthermore, the earlier studies [15,16] presented a limitation regarding the range of input parameters, especially concerning the compressive strength of concrete. This means that the computational models generated from the smallest database present limitations in the results of the pull-out strength when tested with values different from those used for training the model.

This project focuses on the use of computational intelligence - a non-destructive approach - to analyze and develop a prediction model for the steel-concrete bond using an artificial neural network (ANN), emphasizing accuracy and efficiency, and the potential to deal with experimental data. This study aims to contribute to a new model to determine the bond strength, by establishing the maximum applied load.

Artificial Neural Network

ANNs are a typical example of a modern method that solves various engineering problems that cannot – or, at least, easily – be treated by traditional methods. The neural network can collect, memorize, analyze and process a large amount of data obtained through experimental tests [24,25]

ANNs are one of the most useful computational models used in supervised regression tasks and learning classification. ANNs work primarily with three layers: the input layer, the hidden layers and the output layer. The performance of an ANN depends mostly on the performance of hidden layers.

The number of neurons in the input layer is a pattern usually presented to the neural network. Each neuron in the input layer must represent an independent variable that affects the outcome of the network. Therefore, the number of nodes in the input layer is equal to the number of inputs. The number of neurons in the output layer is directly related to the task that the neural network is performing.

1.1 Activation functions

When ANNs are built, it is vital to consider a suitable model architecture. In an ANN, neurons appear as

$$z = w^T X + b \tag{2}$$

followed by the activation function that determines whether the neuron is dispensed or follows the output presented in the following equation:

$$\hat{y} = a(z) = a(w^T X + b) \tag{3}$$

However, it is necessary to train the neural network to evaluate the results using some function error and to propagate through the neural network by updating weights (*w*) and bias (*b*). Therefore, derivatives of activation functions are used.

Understanding and choosing an appropriate activation function can minimize the most significant problems. Other approaches that can be used are proper normalization, weight regularization, gradient clipping, and the improvement of the architecture model.

In the following, a list of activation functions used in this project is presented:

- **Softplus**: The derivative of the softplus function is precisely the sigmoid function. The softplus function is

$$f(x) = \ln(1 + e^x) \tag{4}$$

- **Linear function (ELU):** The linear function is presented in

$$f(x) = x \tag{5}$$

In the current regression models, ELU was used for the output layer and softplus for the other layers.

Analysis and Results

This work required the acquisition of reliable experimental data to determine the bond between steel-concrete through computational intelligence. The database was obtained from multiple authors [3,17–23]. This database presents 190 experimental tests. Four input parameters and one output parameter were used. The input parameters are as follows

- Concrete compressive strength (f_c);
- Bar diameter (ϕ);
- Anchorage length (L_d);

- The surface geometry of ribbed steel bars.

The output parameter is the maximum applied load (in kN).

The database used shows the maximums and minimums of input and output components, as presented in Table 1.

Table 1: Range of experimental data

Input and Output Parameters	Values	
	(Minimum)	(Maximum)
Compressive strength of concrete (MPa)	16,7	100
Diameter (mm)	6	10
Anchorage length (mm)	30	100
Maximum applied load (kN)	1,7	51,7

The types of surface geometry of steel bars present in this study are ribbed (type 1) and notched (type 2), as shown in Fig. 2.

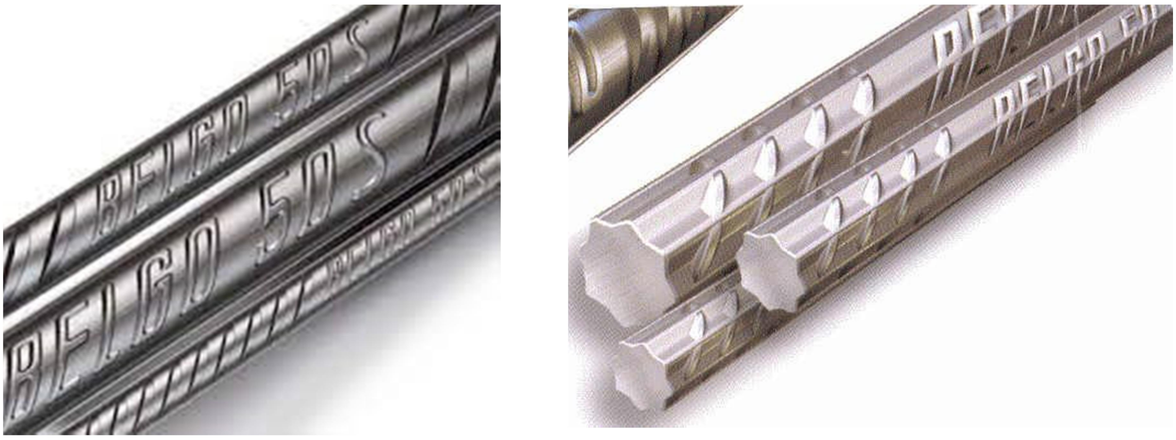

Fig. 2: Steel types of bars: (a) ribbed and (b) notched [26]

As well as with the bar diameter, the anchoring length and the concrete compressive strength, the geometry of the bar surface is an important factor in determining the pull-out resistance since it has a direct impact on the adhesion of the bar to the concrete block. Bar diameter and anchor length improve the pull-out resistance because it increases the steel-concrete contact surface. The presence of ribs and laminations on the bars improves the bonding between the concrete and the steel bar. The concrete compression strength improves the adherence because it prevents the concrete from breaking between the ribs and the steel laminations.

It was necessary to implement the feature scaling technique to effectively standardize the data used. The test results (output parameter) were statistically evaluated before entering the model since the results obtained in adherence tests usually present high coefficients of variation. Because of this behavior, output values (maximum pull-out load) were selected considering at least five repetitions for each sample. The mean, standard deviation, and coefficient of variation for each sample were also evaluated, and the values considered outliers were removed. This statistical evaluation was done to improve the convergence of the computational model.

With the presented data analysis, the adequate architecture of the computational model was developed. Fig. 3 shows the original and predicted values for the test data and Fig. 4 shows the predicted and original scatter values of bond strength test data for the proposed model. The value found for R^2 is equal to 0.94 and the RMSE is equal to 2.35 kN. These figures reveal that the model used presents excellent agreement and results.

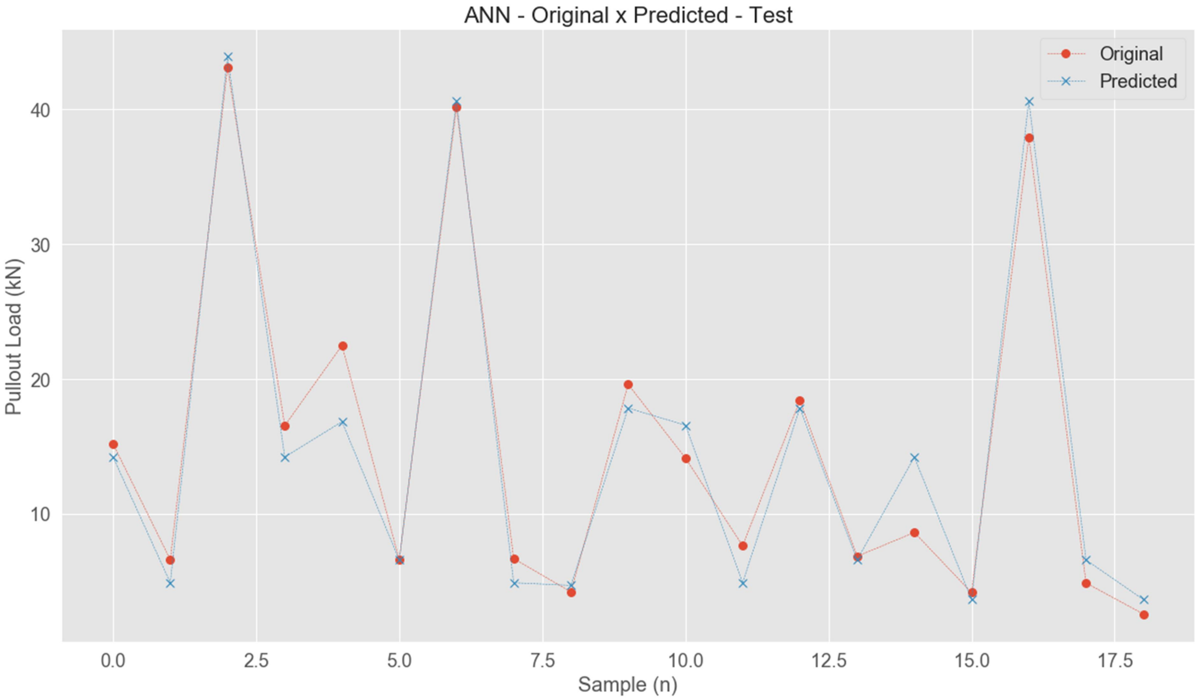

Fig. 3: Original versus expected results for ANN.

Fig. 4: Scatter of predicted and experimental values of bond strength.

The results obtained in this study are summarized in Table 2.

Table 2: Obtained results for ANN.

	RMSE (kN)	**R^2**
ANN	2.35	0.94

Conclusions

This work aimed to present the study of computational intelligence applied to define the bond strength from an original database obtained by multiple authors. A machine learning method, known as an artificial neural network, is used to find the maximum applied load. Data pre-processing and visualization methods were also used to improve the results.

The obtained results for the ANN show the best performance (RMSE = 1.35 kN and R^2 = 0.94). The computational intelligence model used is reliable to solve different complex problems, such as prediction problems. These models can be used to solve a specific problem when a deviation in available data is expected and accepted, and, also, when a defined methodology is not available. Therefore, to predict the properties of concrete, such as a steel-concrete bond, with high reliability, conventional models can be replaced by computational intelligence models instead of using expensive experimental investigations.

Computational intelligence models can be used to predict the bond strength of concrete specimens, as shown in this study. The average errors found for the values predicted by the ANN and those predicted experimentally are highly consistent. Thus, the current study suggests an alternative approach to evaluate bond strength as opposed to destructive testing methods.

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