The prediction of bond strength between thin steel bars to concrete using an adaptive neuro-fuzzy inference system

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Abstract. In reinforced concrete, the solidary behaviour between steel and concrete means that tensile, compressive, bending, or torsional stresses are transferred from one material to another due to adhesion. Tests such as pull-out and beam tests, proposed by the EN:10080 standard, can be used to verify this behaviour; however, the difficulties inherent in destructive tests, as well as the non-linearity and number of variables involved in this issue, make it pertinent to use alternative methods. Using a database with experimental results from pull-out tests, the aim is to create an alternative technique to these tests. Hence, this work proposes using an adaptive neuro-fuzzy inference system to predict the maximum adhesion load in pull-out tests. An adaptive neuro-fuzzy inference system is a hybrid model comprising two techniques artificial neural networks and fuzzy logic. The combination of ANN and fuzzy logic is a useful approach to obtaining the benefits of these systems in a single model of these systems in a single model, namely neuro-fuzzy. The neuro-fuzzy inference system implemented in this work consists of four input series: the surface of the bar, the diameter of the bar (ϕ), the compressive strength of the concrete (f_c), and the length of the anchor (L_d). The output is the maximum adhesion force at the steel-concrete interface. The performance metrics obtained are evaluated against those obtained by other computational methods carried out earlier by our research group. The study indicates an alternative to the destructive tests that are widely carried out, overcoming their limitations considering the safety coefficients used in engineering.

Keywords: Intelligent Systems, Machine Learning, Artificial Neural Network, Fuzzy Logic, ANFIS.

1 Introduction

The solid behaviour of steel and concrete is essential for the structural performance of reinforced concrete. Solidary attitude is known as adhesion or meshing between the materials. This comportment results from the combination of several variables from both materials. In this conduct, concrete resists compressive forces while steel resists tensile forces. Among the essential aspects of the adherence phenomenon are: accession, anchoring, compatibility of deformations, cracking, and fatigue behaviour. Adhesion is the phenomenon that allows the transfer of forces between materials and is essential for the solidary conduct of components. Adherence is affected by various factors such as the surface of the steel bar, i.e., by the area of contact and friction between the materials. Other factors that affect adhesion include concrete compressive strength, steel bar diameter, and anchorage length.

Anchorage is the attachment of the steel bar to the concrete, expressed by the anchorage length, which must be the minimum length necessary to guarantee the efficient transfer of stresses between the materials. During the solidary attitude in the adherence phenomenon, the compatibility of deformations between the components is guaranteed, which means that, for them to work in a solidary manner they must deform in a compatible way and elongate or contract to avoid rupture due to sliding or separation.

The concrete must crack to start the bonding process, causing the steel to be called upon. Concrete is susceptible to cracks when subjected to tensile stresses, so once the steel is solicited, it inhibits and limits the propagation of these cracks, thus redistributing stresses along the steel bars, which is fundamental to maintaining structural integrity. In this respect, knowledge of the adhesion attitude between the steel bars and the concrete is essential.

Reinforced concrete structures can be subjected to load cycles throughout the structure's useful life, which can lead to material fatigue, so bonded conduct must ensure that the materials can adequately withstand these cycles without premature failure. The adherence phenomenon is crucial in reinforced concrete constructions, guaranteeing structural safety, material savings, and performance in adverse conditions. Solidary behaviour makes it possible to optimize both materials, reducing costs and improving the efficiency of structures. Another factor to be mentioned is that in aggressive environments or under extreme loads, adhesion is crucial to resist wear, corrosion, and other forms of deterioration.

Standardized methods for measuring adhesion include the following tests: Pull-Out Test, Push-Out Test, Beam Test, Direct Tension Test, and Split-Cylinder Test. The Pull-Out test is standardized by EN, B. S. 10080 [1]**.** This test measures the force required to pull out a steel bar embedded in a concrete block, as shown in Figure 1. In this test, the bar is pulled axially out of a concrete cube until failure occurs due to pulling or cracking of the concrete block. These failures are strongly influenced by several factors, specifically type of reinforcement, surface shape (smooth or ribbed), bar diameter, presence of confining reinforcement, distance between bars, coating, and concrete quality.

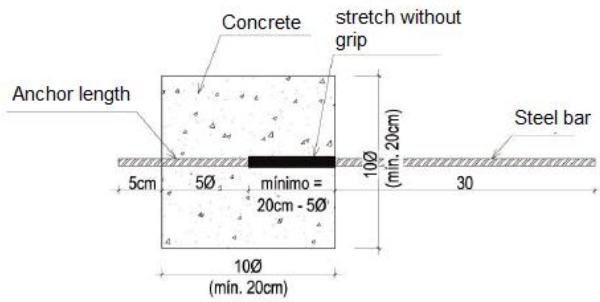

Figure 1. Specimen model according to EN:10800

Adherence can be broken down into several parts: adhesion by chemical adhesion, adhesion by friction, and mechanical adhesion. Mechanical Adherence is the mechanical interaction between steel and concrete, due to the presence of protrusions on the bar´s surface (ribs or surface dents), which act as support pieces, mobilizing the compressive stresses in the concrete.

The methods illustrated are considered experimental, which involve using full-scale physical prototypes to investigate the phenomenon under study. These methods provide high-quality results but require a significant investment in the manufacture of the specimens and the infrastructure needed to simulate the experiment.

The adhesive stress can be obtained through normative prescriptions. The normative methods prescribed in NBR 6118 (ABNT, 2023), the Spanish standard UNE 36740, the French standard BAEL-91, and the CEB (1970) are considered relevant. The normative models have in common that they adopt uniform bond stress across the entire surface of the bar. Although widely used, they do not represent the physical phenomenon of bonding. The adherence phenomenon creates a bulge of tensile and compressive stresses in the region adjacent to the bar.

Thus, even taking into consideration parameters such as f_{ck}, diameter, adhesion situations, weighting coefficients, steel grade, age, bar surface, and experimental parameters, the normative prescriptions or the theoretical model do not represent the physical phenomenon. Alternative methods, therefore, become important in this area. The number of variables involved in the adhesion phenomenon is high and the relationship between these parameters is non-linear, which makes it difficult to determine the maximum steel-concrete adherence force using conventional methods. Hence, machine learning algorithms are alternative techniques for overcoming these limitations. Artificially intelligent systems have proven effective in solving real-life problems, particularly for non-linear tasks, as shown in Hoang et al., 2019 [2].

Several studies have dealt with intelligent systems to predict the mechanical and behavioural characteristics of materials used in construction. When it comes to accession, the method must be able to relate the value of the maximum adhesion force and the relative displacement between the materials. These factors are the output of the pull-out test standardized by EN, B. S. 10080 [1]. Whatever the input parameters, the computational method must relate the input parameters to the output parameters, thus breaking down the limitations, including the non-linearity of the phenomenon. Regardless of the database used, the quantity and quality of the input parameters define the mechanical characteristics, especially of reinforced concrete.

This research group has developed machine learning algorithms for predicting the maximum adherence force, especially when using thin bars (diameter less than 10 mm). These include [3,4,5,6,7]. The database used in these methods comes from experimental tests carried out by Carvalho et al., 2017 [8]. The adherence parameters in this database are bar type and diameter, concrete compressive strength, anchorage length, and maximum adherence force.

Several studies have been carried out on the use of intelligent systems to predict the mechanical characteristics of concrete. In Petkovic et al. [9], the pull-out test was used to determine the shear bond strength; also, subsequent test data was evaluated using ANFIS, as well as surface classification utilizing a laser roughness analyzer, designed particularly to assess the roughness of the concrete substrate. ANFIS was used to optimize the process based on five processing parameters. As a result, this research has created a new non-destructive in situ approach for evaluating the influence on the measurement of the shear strength of concrete layers.

In the work of Pei et al. [10], a hybrid model integrating ant colony algorithms and a fuzzy c-means clustering method in the adaptive neuro-fuzzy inference system (ANFIS) was proposed to predict the strength of the bond between fiber-reinforced polymer (FRP) sheets and the concrete surface under direct tension. The results confirmed that the ANFIS model developed showed greater accuracy than the other models proposed by the author, with a higher coefficient of determination ($R^2 = 0.97$) and a lower root mean square error (RMSE = 1.29 kN).

In Ngudiyono [11], the author states that bond strength is a parameter that is an essential factor affecting the behaviour of reinforced concrete. In this article, the ANFIS model was built to predict bond strength in reinforced concrete. The results of the proposed model showed good agreement with the experimental results, as evidenced by an R^2 of 0.71 and an RMSE of 3.31 MPa in the test data.

Alizadeh [12] described that corrosion attributed to different environments is one of the serious problems encountered in steel reinforcement bars. In this work, the strength of the connection between the GFRP bars and the concrete is predicted using the neuro-fuzzy inference system and artificial neural networks. The proposed neuro-fuzzy inference system consisted of five inputs and the connection resistance as an output, with the predicted value being compared with normative instructions such as ACI 440.1R-15 and CSA S806-12. It was concluded that the results are more compatible with the experimental results when compared to those obtained in the code equations.

The expansion of the precast industry and the increase in slender structures with the application of high-strength concrete has led to a growing demand in the construction sector for thin bars. It is therefore important to carry out studies to assess the adhesion of this type of bar to concrete. This study proposes an intelligent neuro-fuzzy inference system to solve this problem and to create a new approach to determining steel-concrete bond strength by predicting the maximum bond load, thus overcoming the limitations of destructive laboratory tests, and the non-linearity of the parameters involved.

2 Methodology

2.1 Data Description and Preprocessing

The database used as the basis for this work comes from the study by Arruda *et al.*, [13] where the data from Carvalho *et al.*, [8] was processed using statistical techniques to remove outliers. Two methods were used in this analysis: the Grubbs test and an evaluation of each sample's average values and standard deviation. The experimental program used concrete classes C25, C35, and C40; CA-50 ribbed bars (with diameters of 6.3, 8.0, and 10 mm), and CA-60 notched bars (with diameters of 5.0, 6.0, 8.0, and 9.5 mm). This database checks four input parameters: concrete compressive strength (f_{ck}), bar diameter (ϕ), anchor length (L_d), and the surface geometry of the steel bars. The output parameter is the maximum applied adhesion load (N).

2.2 The Adaptive Neuro-Fuzzy Inference System

The Adaptive Neuro-Fuzzy Inference System is a machine learning model based on the fuzzy theory, developed by Zadeh [13], per Figure 2. The theory re-signifies the classical set theory since it deals with the uncertainties of the natural language applied to the theory of sets.

Firstly, a classical set can be characterized by a function $\chi_B(x)$, that assigns a value of 1, if x belongs to the set and 0 if it does not belong. However, when treating real-world problems, sometimes, zeroes and ones cannot describe reality accurately. For example, to classify whether someone is tall or not, using the classical theory, the approach could be to set a minimum height and, if a person is higher than the minimum, they belong to the 'tall' set; else, they are on the 'not tall' set. Otherwise, using the fuzzy theory, a person would be classified depending on how close they are to that minimum, i.e. how tall they are, instead of just being considered 'tall' or 'not tall'. In this example, the minimum height is the *fuzzy rule* - an IF-THEN statement - used to infer the output ('tall' or 'not tall') based on the input (a person's height). Thus, a fuzzy set can be characterized by a *membership function* $\varphi_A(x)$, that associates, to each element, a value on the interval $[0,1]$. Basically, the fuzzy model extends the codomain of the function that characterizes a classical set, thereby, adding grades of membership to the classical theory.

Therefore, the fuzzy theory can be combined with a machine learning model to create a powerful system, capable of dealing with classification and regression problems. The Adaptive Neuro-Fuzzy Inference System (ANFIS), according to Salleh et al [16], combines the learning abilities of Artificial Neural Networks (ANN's) and the ability to represent real information from fuzzy theory. The architecture of an ANFIS system is presented in Figure 3. This union creates a model that can be easily understood (because it deals with natural language) while producing good predictions.

The ANFIS model uses the concept of layers and forward-propagation from the ANN's and adds on the fuzzification process, which uses some predefined fuzzy rules to convert the inputs in values in the interval $[0,1]$. In this way, the information is processed by the network that, in the end, deffuzyfies the information and returns a final value (in regression problems).

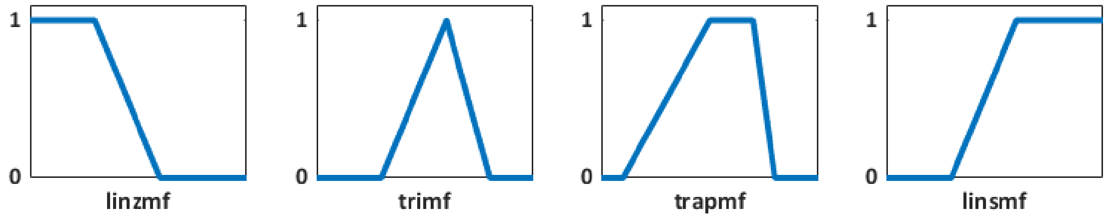

Figure 2. Examples of linear membership functions

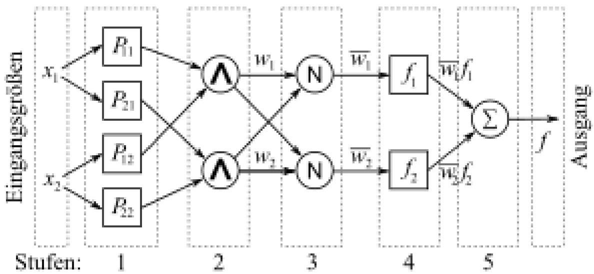

Figure 3. Anfis architecture

2.3 Performance Metrics

As mentioned, $\boldsymbol{RMSE_i}$, given by Equation (1), $\boldsymbol{ERROR_i}$, as per Equation (2), and $\boldsymbol{CV_i}$, given by Equation (3) and $\boldsymbol{Indicator}$ as per Equation (4), are used as performance metrics. In the equations, $\boldsymbol{y_i}$ is the observed value of sample, $\bar{\boldsymbol{y}}$ is the mean of the observations of sample, $\hat{\boldsymbol{y}}$ is the predicted value of $\boldsymbol{y_i}$ of sample, $\boldsymbol{\sigma_i}$ sample standard deviation of sample, $\boldsymbol{i}$ sample number and $\boldsymbol{N_i}$ is number of sample members.

$$RMSE_i = \sqrt{\frac{1}{N_i}\sum_{i=1}^{N_i}(y_i - \hat{y})^2} \tag{1}$$

$$ERROR_i = \frac{RMSE_i}{\hat{y}_i} \tag{2}$$

$$CV_i = \frac{\sigma_i}{\bar{y}_i} \tag{3}$$

$$Indicator = \frac{RMSE_{all\ data}}{\bar{y}} \tag{4}$$

The metrics proposed in this work are innovative compared to other work carried out by other authors. In this way, it proposes metrics that are different from those used so far.

3 Presentation and analysis of the results

3.1 The dataset results

Once the database had been treated with the removal of outliers available in Arruda et al [10], it was subdivided into 17 samples according to the similarity of their data. Figure 4 shows the average pull-out forces and the standard deviations observed for each sample. Studies of statistical parameters are present in situations such as strategies and planning, data collection and organization, analysis, and clear and objective interpretation of the observed data. The coefficient of variation is used to analyze dispersion in terms of the average value. It is a way of expressing the variability of the data excluding the influence of the order of magnitude of the variable. The coefficient of variation (CV) is used to ensure quality and to assess reproducibility and repeatability of a test. As the CV analyzes dispersion in relative terms, it is given in %. The lower the value of the coefficient, the more homogeneous the data. It is mainly used in two situations: to compare a set of data with very unequal means and to compare data with different units.

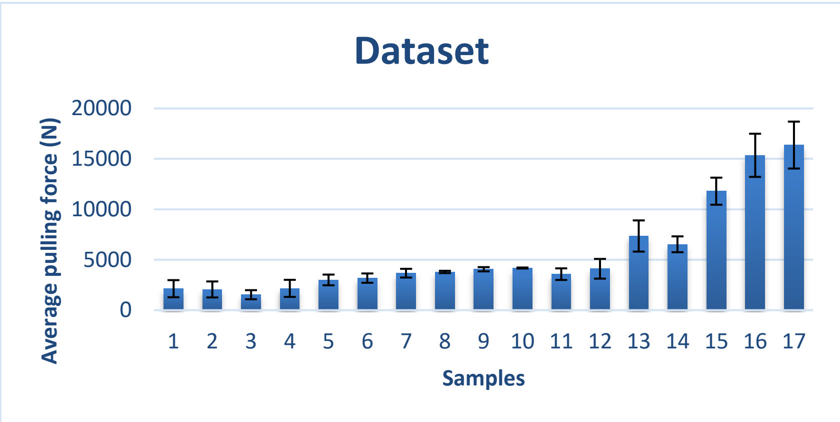

Figure 4. Average pulling force x samples

3.2 The Adaptive Neuro-Fuzzy Inference System results

In the analysis of computational methods, it is common to use general metrics to analyze the performance of an intelligent system. Predicted values are obtained from the simulation and metrics such as RMSE and R^2 are calculated. The ANFIS machine learning technique proved to be effective in predicting adhesion strength. The results obtained for this intelligent system had an RMSE of 1166.08 N and a coefficient of determination of 0.95, this value was obtained by the metric corresponding to all the data, per Figure 5.

The values shown in Table 1 refer to the RMSE values calculated for each sample due to the variety of samples and the Error for each sample in the database. Table 1 shows the CV of each sample set. For notched bars, the CV values show averages of 37%, 15%, 4%, and 9% for diameters of 5 mm, 6 mm, 8 mm, and 9.5 mm, respectively. The 5 mm bar presented the worst CV in this data set, which can be explained by the difficulties inherent in the test, i.e., concrete a 5 mm bar in a 200 mm specimen and ensuring the correct anchoring length. For ribbed bars, the coefficient of variation averaged 22.5%, 11.5%, and 14% for diameters of 6.3 mm, 8 mm, and 10 mm respectively. In ANFIS, for notched bars, the error value yielded averages of 33%, 13%, 3%, and 8%, for diameters of 5 mm, 6 mm, 8 mm, and 9.5 mm, respectively. For ribbed bars, the error averages were 19%, 10%, and 13% for diameters of 6.3 mm, 8 mm, and 10 mm, respectively. Table 2 shows the average values achieved, RMSE as well as the calculated indicator values.

Table 1. Metrics of the dataset attributes.

INPUT DATA					STATISTICAL PARAMETERS				ANFIS	
i	Bar type	Ø (mm)	fck (Mpa)	Lb (mm)	$\bar{y}_i$(N)	σ_i (N)	CV_i	N_i	$RMSE_i$ (N)	$ERROR_i$
1	Notched CA-60	5	29,05	25	2127,88	848,60	0,40	6	780,08	0,38
2	Notched CA-60	5	27,9	25	2052,68	794,81	0,39	5	721,29	0,33
3	Notched CA-60	5	41,55	25	1533,32	451,38	0,29	5	405,31	0,26
4	Notched CA-60	5	45,3	25	2161,13	849,23	0,39	4	738,41	0,35
5	Notched CA-60	6	28,25	30	2997,20	530,31	0,18	4	459,27	0,15
6	Notched CA-60	6	28,9	30	3177,98	461,89	0,15	5	413,73	0,13
7	Notched CA-60	6	45,1	30	3666,93	433,69	0,12	4	377,63	0,10
8	Notched CA-60	8	31,6	40	3790,75	114,34	0,03	2	82,45	0,02
9	Notched CA-60	8	40,1	40	4056,10	209,85	0,05	4	182,03	0,04
10	Notched CA-60	9,5	30,2	47,5	4179,93	47,06	0,01	4	41,18	0,01
11	Notched CA-60	9,5	41,4	47,5	3570,23	575,93	0,16	4	505,18	0,14
12	Ribbed CA-50	6,3	22,8	31,5	4102,08	977,30	0,24	**6**	798,00	0,19
13	Ribbed CA-50	6,3	46,95	31,5	7353,02	1546,31	0,21	5	1398,11	0,18
14	Ribbed CA-50	8	29,5	40	6530,18	786,86	0,12	5	707,13	0,11
15	Ribbed CA-50	8	46,6	40	11797,00	1341,82	0,11	3	1095,63	0,09
16	Ribbed CA-50	10	27,9	50	15353,89	2139,94	0,14	9	2032,48	0,13
17	Ribbed CA-50	10	45,3	50	16370,44	2326,07	0,14	9	2201,50	0,13

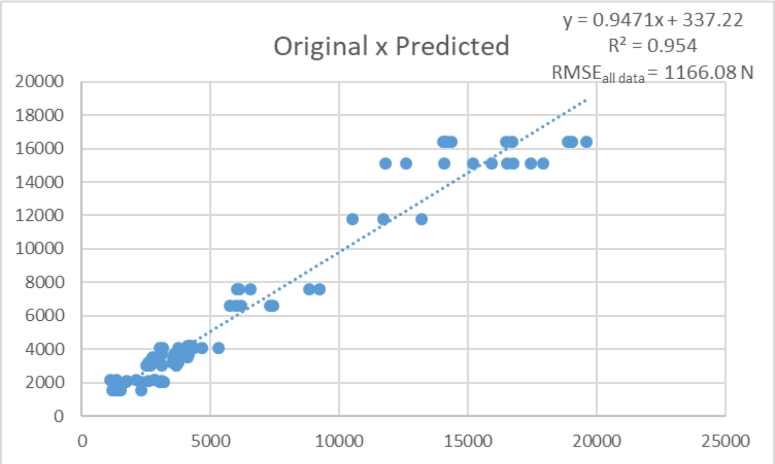

Figure 5 - Target x Forecast results for the ANFIS

Table 2 - Indicator

	Database attributes	Values		Indicator
		Average	RMSE	ANFIS
IN THIS WORK	Bond strength (N)	6596,76	1166,08	0,177
KUMAR(2023a)	Bond strength (kN)	14,85	3,54	0,238
NGUYEN (2021)	Bond strength (kN)	14,92	3,38	0,227
SHBEEB (2024)	FRP Bond strength (MPa)	8,15	1,07	0,132

The indicator is calculated using the RMSE for the entire database and is expressed only for this value. The indicator is used to evaluate the algorithm's performance. Based on the main metrics normally used, it indicates a value that represents the program's ability to predict the values obtained in experimental work, per Table 2. The result obtained in table 2 for this work takes as input the RMSE value obtained via the intelligent system, which is an RMSE of 1166.08 N. It is important to emphasize that, even if the experimental values show great dispersion, the indicator has reproduced the same dispersion in the values obtained by the algorithms. In this study, an indicator value of around 18% was obtained, in Kumar's study 24%, Gguyen's 23%, and Sheeb's 13%.

4 Conclusions

This work aims to predict the maximum steel-concrete bond strength using thin bars in pull-out tests. The database used was previously processed to remove extraneous data. The Adaptive Neuro-Fuzzy Inference System was used as an intelligent system and once implemented, the values and the performance metrics were predicted. The results were compared using the coefficient of variation of the test and the error obtained by the simulation, showing a strong trend: the better the coefficient of variation of the test, the better the algorithm performance. Finally, based on the results presented, the machine learning algorithm can satisfactorily predict the strength of the steel-concrete bond of the samples in pull-out tests on thin bars. In continuation of this work, other intelligent systems will be proposed, as well as the proposal of a hybrid method using some machine learning algorithms, or even computational heuristics in order to predict the bond strength between steel and concrete.

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