A Computational Approach to Predict the Bond Strength of Thin Steel Rebars in Concrete by Means of Support Vector Machine

Priscila F. S. Silva[1], Gray F. Moita[1], Eliene P. Carvalho[1], Vanderci F. Arruda[1]

[1] *Centro Federal de Educação Tecnológica de Minas Gerais*
Programa de Pós-Graduação em Modelagem Matemática e Computacional
Av. Amazonas, 7675, Nova Gameleira, 30.510-000, Belo Horizonte, MG, Brazil.
201422800040@aluno.cefetmg.br; gray@dppg.cefetmg.br; eliene@cefetmg.br; vanderci-engcivil@hotmail.com

Abstract. The bond strength between steel bars and concrete is one of the essential aspects of reinforced concrete structures and is generally affected by several factors. 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 89 pull-out specimens to develop a support vector machine (SVM). The data used in the modeling was arranged as four input parameters: bar surface, bar diameter (ϕ), concrete compressive strength (f_c) and the anchorage length (L_d). 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 5.0-, 6.3-, 8.0- and 9.5-mm diameters, usually used in reinforced concrete elements. This work uses SVM 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 applied load in the pull-out test was 1.305 kN and the R-squared was 0.95. Therefore, this study can conclude that the current model can satisfactorily predict the bond strength of thin bars.

Keywords: Steel-concrete bond, Thin rebars, Support vector machine.

1 Introduction

Steel-concrete bonds are essential for the structural behavior of reinforced concrete structures and an extensive range of parameters can influence the characteristics of the steel-concrete interface [1]. Many authors have conducted experimental investigations for the most critical parameters influencing the bond. The bond characteristics are usually affected by the bar diameter, the anchorage length of bars, the concrete compressive strength, and the bar surface [2], [3]. As a phenomenon influenced by many variables, it is challenging to establish how the steel-concrete adhesion can be described in standards used for reinforced concrete design [4].

Several scientific studies on this property have been performed since the 1940s [5], [6], among many other studies in this field. Generally, these studies refer to bars with diameters greater than 12.0 mm [7], [8]. However, few researches have evaluated the performance of reinforcing bars with diameters smaller than 10.0 mm, which includes 5.0-, 6.3-, 8.0- and 9.5-mm diameters, generally used in reinforced concrete elements [9].

One of the most used tests to evaluate the steel-concrete bond is the pull-out test described in RILEM-CEB RC [10]. The pull-out test extracts 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 force measured at one end while 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.

Although Eq. (1) can be used to predict the value of the bar pull-out stress, the value of the load *P* is usually predicted by the pull-out test, with expensive destructive testing methods.

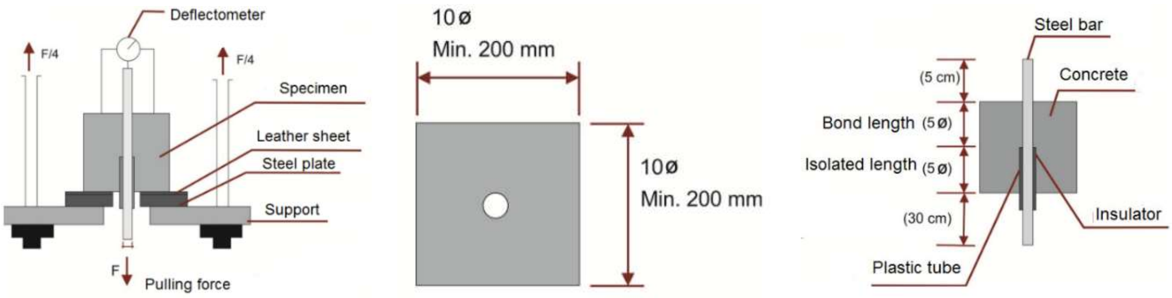

Fig. 1: Pull-out test set-up [10]

The size effect of rebars in the bond has been illustrated direct or indirectly by some researchers. Some of them discussed the issue of size effect on the steel-concrete bond, including the 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.

Technological advancement usually allows engineering problems to be solved with machine learning, and its applications being 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 by implementing and testing new computational models to predict 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 in designing structures for civil engineering [12]–[14]. The steel-concrete bond has also been an object of study using artificial intelligence in some works, but usually with rebars diameter greater than 10 mm [15]–[17]

This project uses computational intelligence to analyze and develop a prediction model for the steel-concrete bond using a support vector machine method, emphasizing accuracy, efficiency, and the potential to deal with experimental data. This study contributes to a new model to determine the bond strength by establishing the maximum applied load using a support vector machine (SVM).

2 Support Vector Machine

Support vector machine is a popular learning algorithm that works in classification and regression problems, in addition to performing linear regression and classification [18]-[19]. To sort linearly separable data, there may be different hyperplanes that can separate the data (Fig. 2). The problem is finding a hyper-plane (margin) that could maximize the separation between two classes [20].

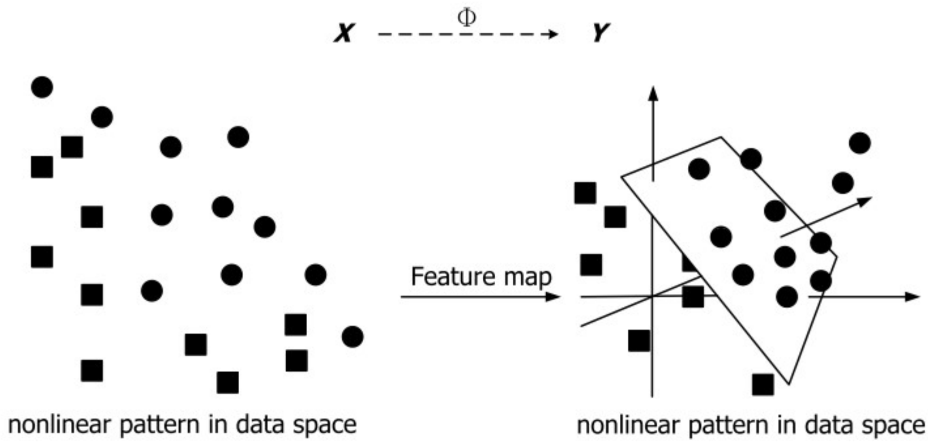

Fig. 2: Nonlinear-to-linear model mapping [21]

In SVM regression, the input is first mapped onto an m-dimensional feature space by fixed (nonlinear) mapping. A linear model is constructed in this feature space. The linear model in the feature space, *f(x,w)*, can be expressed in mathematical notation as show in Eq (2):

$$f(x,\omega) = \sum_{j=1}^{m} \omega_i g_i(x) + b \tag{2}$$

where $g_j(x)$, j = 1, …, m is the set of nonlinear transformations; and b is the "bias" term.

Data are often assumed to be mean zero and can, therefore, be obtained in the preprocessing stage, so that the bias term is dropped. Estimation quality is measured by the loss function $L[y,f(x,\omega)]$. The SVM regression employs the following ε-insensitive loss function, proposed by Vapnik [22]:

$$L_\varepsilon[y, f(x,\omega)] = \begin{cases} 0 \ if \ \left|y - f(x,\omega)\right| \le \varepsilon \\ \left|y - f(y,\omega)\right| \ otherwise \end{cases} \tag{3}$$

Linear regression is performed in SVM regression in the high-dimension feature space by using insensitive loss and reduces model complexity by minimizing $||\omega||^2$.

This paper used a support vector regressor as a non-parametric regression technique that relies solely on kernel functions. This technique builds a multidimensional hyper-plane space to separate a dataset into different classes.

As the dataset is a multivariate supervised dataset, some of the kernels used for regression comparison could be linear, polynomial, or RBFs [23]. In this project, the GridsearchCV, a function which implements a score method whose parameters are optimized by cross-validated, is used to evaluate these possible kernelsThus, it is possible to assess the performance of these kernels and evaluate different parameters of ε, which are the penalty parameters for the error.

For polynomial and RBF kernels, there is a γ parameter called the kernel coefficient. The best performance is evaluated based on the results of R-squared. Thus, it is possible to assess the best attained results of the implemented model using different kernels, ε values and γ parameters.

3 Analysis and Results

This work required the acquisition of reliable experimental data to determine the bond steel-concrete through computational intelligence. The database chosen was obtained from Carvalho et al. [4]. This database presents 89 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).

In order to assess data dispersion, the data range is shown in Table 1.

Table 1: Data Range

Model attributes	**Values**	
	(Minimum)	(Maximum)
Compressive strength of concrete (MPa)	23	47
Diameter (mm)	6	10
Anchorage length (mm)	30	100
Maximum applied load (kN)	2.51	36.45

The types of surface geometry of steel bars present in this study are ribbed (type 1) and notched (type 2), as show in Fig. 3.

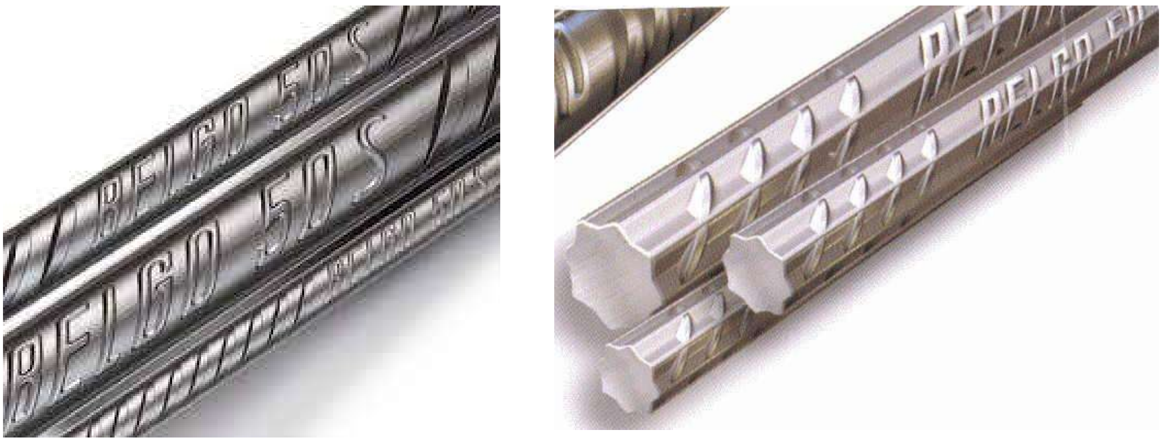

Fig. 3: Steel types of bars: (a) ribbed and (b) notched [24]

The presented data provided by Carvalho et al. [4] are consolidated and distributed adequately for input and output variables. Still, 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 force) 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 in order to improve the convergence of the computational model.

For the SVM learning model, the best parameters to be used in the kernel were defined. As GridsearchCV was used to evaluate possible kernels, linear, polynomial and RBFs could be applied. The intention was to evaluate the performance of these kernels in the dataset presented and estimate different parameters of ε, which are the penalty parameters for the error. For polynomial and RBF kernels, there is also a kernel coefficient called the γ parameter. In such cases, there is a need to search these parameters to find the relationships between them and the best metrics to predict relevant results for the database optimally.

By applying linear, polynomial and RBFs, it was found that the RBF was the best SVM kernel, i.e., which best predicts the results for the data presented. The best performance is evaluated based on the results of R^2. Thus, it is possible to evaluate the best performance of the model over different kernels, ε values and γ parameters. Table 2 presents the range of parameters used in the GridsearchCV and the best parameters used in the experiments for the SVM algorithm.

Table 2: Range of parameters used and best parameters for the SVM experiments

Parameter	Range	Setting
C	10-500	500
Degree	3-5	3
Epsilon	0.1	0.1
Kernel	RBF-Linear-Sigmoid	RBF

With the presented data analysis, the adequate architecture of the computational model was developed. Fig. 4 shows the original and predicted values for the test data and Fig. 5 shows the predicted and original scatter values of bond strength test data for the proposed SVM model. The value found for R^2 is equal to 0.95 and the RMSE is equal to 1,305kN. These figures reveal that the model used presents excellent agreement and results.

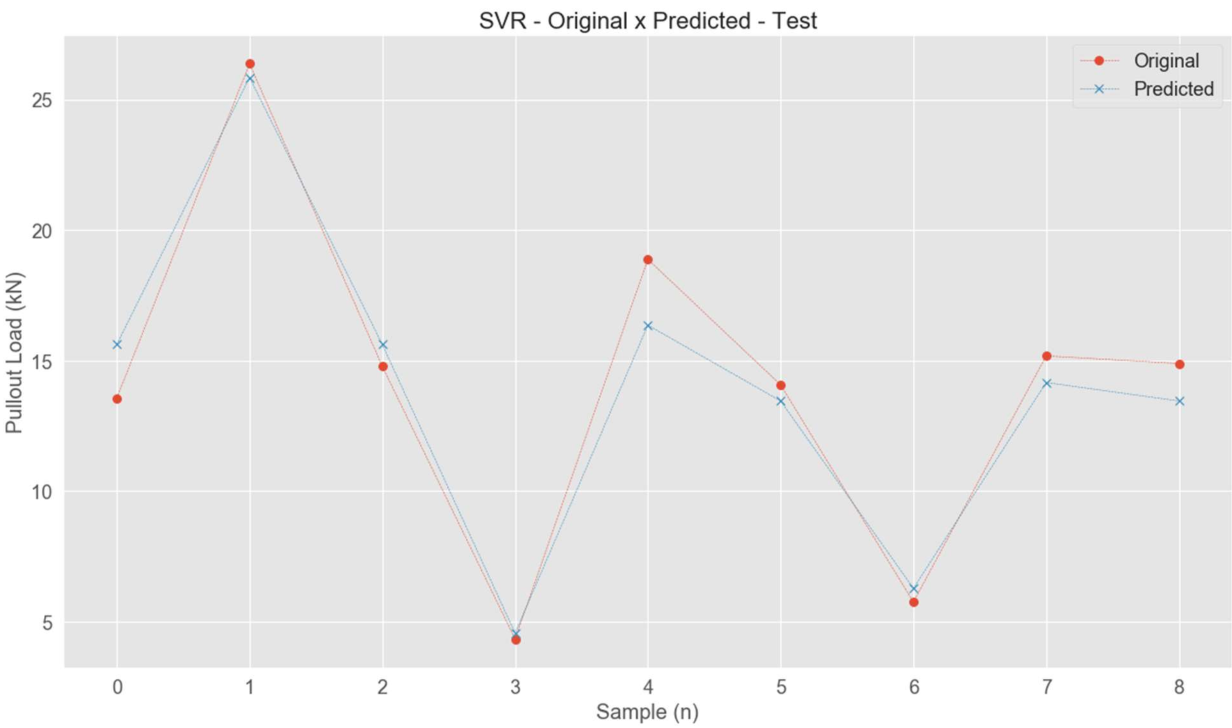

Fig. 4: Original versus obtained results for SVM.

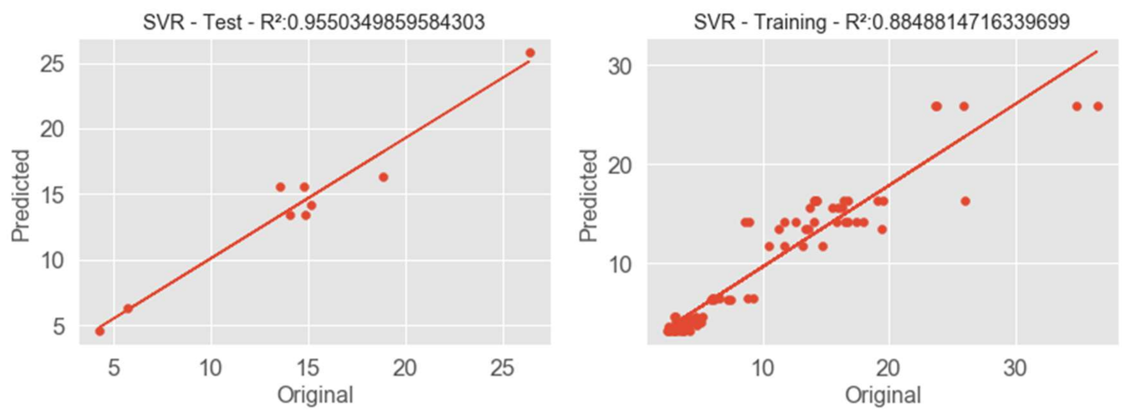

Fig. 5: Scatter of predicted and training (original) experimental values of bond strength.

The results obtained in this study are summarized in Table 3.

Table 3: Obtained results for SVM.

	RMSE (kN)	**R^2**
SVM	1.305	0.95

4 Conclusions

This work aimed to present the study of computational intelligence applied to define the bond strength from an original database obtained by Carvalho et al. [4]. A machine learning method, known as Support Vector Machine (SVM), is used to find the maximum applied load. Data pre-processing methods were also used to improve the results.

The obtained results for best performance of the SVM are RMSE = 1.305kN and R^2 = 0.95. The computational intelligence model used is reliable to solve different complex problems, such as the prediction pull-out load of thin bars in concrete specimens. These models can be used to solve a specific problem when a deviation in available data is expected and accepted and 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.

At the end, the average errors found for the values predicted by the SVM and those predicted experimentally are highly consistent. Thus, the current study suggests an alternative approach to evaluating bond strength instead of expensive destructive testing methods.

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