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Evaluation of code formulations for NSM CFRP bond strength of RC elements

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SUMMARY

This paper presents an analytical analysis which intends to verify the accuracy of existing code formulations for predicting the pullout strength of NSM CFRP systems applied to concrete. A database with a limited set of parameters was gathered and two code formulations were tested on it. Then, a new approach was tested. This uses Data Mining algorithms to develop models to predict the pullout strength based on user chosen parameters. The results reveal that existent code formulations aren't as accurate as expected and that Data Mining can be a sound alternative or, at least, a good complement since it can also help know and understand the key parameters with relevant influence on the pullout strength of such strengthening systems.

1. INTRODUCTION

In the context of strengthening concrete structures, fiber reinforced polymers (FRPs) have been emerging in the last decades as a sound alternative to traditional materials. High stiffness and tensile strength, low weight, easy installation procedures, high durability (no corrosion), electromagnetic permeability and practically unlimited availability in terms of geometry and size are the main advantages of the FRPs [1].

One of the most promising techniques to apply FRPs on concrete structures is the near-surface mounted (NSM) technique, which consists on the installation of FRP laminates or rods into grooves opened on the concrete cover [2].

American Concrete Institute (ACI) [3] and Standards Australia (SA) [4] have proposals for predicting the strength of NSM systems. These are based on regression analysis of existing experimental data. Both formulations use different input parameters which reflect the uncertainties that still remain on which parameters have more influence and can better describe the complex phenomena associated to this technique. Moreover, the simple fact of using a single expression with a limited number of input variables to describe the NSM bond strength introduces a certain level of error. In order to address this kind of problems, Data Mining (DM) techniques have been used with success [5,6].

DM is a relatively new area of computer science which combines different computational techniques like statistics, machine learning, artificial intelligence and data management, among others, to provide a deeper knowledge about data present in a database. DM is thus emerging as a class of analytical techniques that go beyond statistics and concerns with automatically find, simplify and summarize patterns and relationships within a data set [7].

In this work, the referred code formulations and some DM algorithms are tested on a database of NSM pullout tests.

2. ANALYTICAL ANALYSIS

The following sections present a brief overview on the formulations used in the analytical analysis, both the existent code formulations and the DM algorithms.

2.1 NSM formulations

As previously referred, two code formulations for the analysis of NSM FRP systems will be addressed in this work, ACI and SA, namely. Both proposals are based on the same philosophy: if the bonded length is sufficient enough (development length), entire bond force will be mobilized, otherwise, this force will be linearly reduced with the actual bond length.

Table 1 presents the main aspects of the referred formulations. In this table, letters *A*, *b*, *d*, *E*, *f*, *L*, *N* and τ, are cross section area, width, depth, modulus of elasticity, tensile/compressive strength (FRP/concrete), length, axial force and bond strength, respectively, while *c*, *f*, *g* and *b*, are indexes related to concrete, FRP, groove and bond properties, respectively. The definition of the geometrical parameters of interest can be seen in Figure 1. In this figure, L_{per} is the perimeter of the failure surface located 1 mm away from the groove perimeter.

Table 1: Code formulations for NSM FRP bond strength of RC elements.

Code	Development Length [mm]	Bond Strength [kN]	Comments
ACI	$L_{b,\bigcirc} = \dfrac{d_f f_f}{4\tau_b}$ $L_{b,\square} = \dfrac{b_f d_f f_f}{2(b_f + d_f)\tau_b}$	$N_b = f_f A_f$	$\tau_b = 6.9$ MPa ○ circular bar □ rectangular bar
SA	$L_b = \dfrac{\pi}{2\sqrt{\dfrac{\tau_m L_{per}}{\delta_m E_f A_f}}}$	$N_b = \alpha 0.85 \varphi_{per}^{0.25} f_c^{0.33} \sqrt{L_{per} E_f A_f}$	$\tau_m = \left(0.802 + 0.078\varphi_{per}\right) f_c^{0.6}$ $\delta_m = \dfrac{0.976\varphi_{per}^{0.526}}{\left(0.802 + 0.078\varphi_{per}\right)}$ $\alpha = 1.0$ for mean N_b $\varphi_{per} = d_{per} / b_{per}$ $N_b \le f_f A_f$

In order to check which of the variables have more influence in the prediction of the pullout strength, a simple direct analysis was made. This consisted in plotting pullout strength as a function of each parameter and look for the determination coefficient (usually designated by R^2). From that analysis, it was concluded that bond length (L_b), depth of the groove (d_g) and FRP (d_f) and perimeter of the groove (P_g) and FRP (P_f), were the most influent variables. Then, in a pure mathematical approach (not considering the physical meaning), those five variables, all in mm, were combined with each other and the prediction model presented in Equation (1) was obtained.

$$N_b = 0.065\left(L_b P_f P_g\right)^{0.52} \tag{1}$$

In order to have a more physical meaning in the analysis, the five variables that were previously found as having critical influence on the pullout strength prediction were used, in a different approach, with the addition of concrete cylinder strength (f_c in MPa) and axial rigidity of the FRP ($E_f A_f$ in N). With these seven variables a simple multi-linear regression (MR) analysis was carried out and the prediction model presented in Equation (2) was obtained.

$$N_b = -38.5 + 0.3 f_c - 1.6\times10^{-6}\left(EA\right)_f + 0.12L_b - 2.4P_f + 3.1P_g + 9.3d_f - 7.9d_g \quad (2)$$

All this 4 models, ACI, SA and equations (1) and (2), were applied using a database of pullout tests gathered from experimental works available in the literature. This database is introduced in section 3.

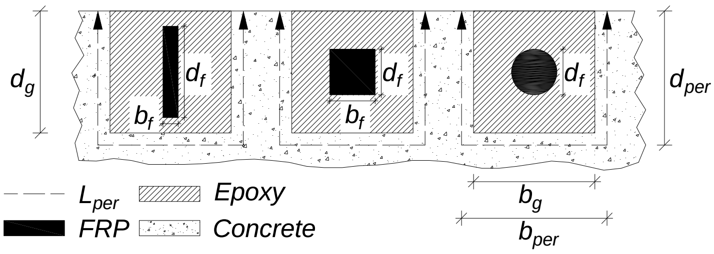


Figure 1: Geometrical parameters used in the formulations in study.

2.2 Data Mining

DM is part of the process of discovering useful knowledge from databases. It consists on the application of specific algorithms for extracting models from data, even if in the presence of data apparently unrelated.

In that context, DM algorithms, use real data from a database of examples of the studied phenomenon, then, by an iterative learning process, the algorithms are capable of predicting the phenomenon behavior when new data is given.

The algorithms tested and analyzed in this work were the Artificial Neural Networks (ANN) and the Support Vector Machines (SVM). They were run on the R program environment [8] which is an open source freeware statistical package. Within this framework a specific routine called RMiner [9] was used.

The referred algorithms can be described as black box algorithms since they don't provide an equation relating the input and output variables. They learn the phenomenon using a training set and can understand the intrinsic and complex (if any) relations between the variables providing a predictive model for new input data. They also provide the relative importance of each of the input parameters in the output results. This fact allows for a deeper understanding of the relations between the different parameters and to analyze if these relations are meaningful and make sense from a physical point of view.

In this work, the database of pullout tests was divided in two subsets with fifty (2/3) and twenty five (1/3) specimens. The first one was used as training set, in which the prediction model is obtained, while the second set was for testing the obtained model.

In addition to this careful division, the algorithms run a preliminary analysis on training data by doing a cross-validation analysis. This consists on randomly partitioning the training data into *k* mutually exclusive subsets randomizing for each one the cases within the training and test set. Training and testing is performed *k* times and the overall error of the model is taken as the average of the errors obtained in each iteration. In this work the value of *k* was 10.

To start the analyses with the DM algorithms, the same seven variables that were previously used in the simple analysis were used again. With these seven input variables, DM algorithms were run and the outputs analyzed. In this stage, it was verified that an over-fitting phenomenon occurred. This can happen sometimes when the ratio between the input variables and the available data is large, which was the case. In order to solve that problem without losing the information, some variables were combined. In the end, the best models obtained, used concrete strength (f_c), axial rigidity of the FRP (E_fA_f) and the product of the other five parameters ($L_bP_fP_gd_fd_g$) as input variables.

In the results section, the main results of two models, one with ANN and other with SVM, using this three input variables, are shown and compared with ACI, SA, MR and Equation (1) models.

3. DIRECT PULLOUT DATABASE

In the scope of this work, a database of 75 single shear direct pullout tests with one carbon FRP (CFRP) bar (24 specimens) or strip (51 specimens) applied with the NSM technique and using epoxy adhesive was gathered from the literature [10-19]. Table 2 presents a summary of the variation of some relevant parameters of that database. The failure modes of the specimens in this database include concrete splitting (27 specimens), epoxy splitting (3), FRP rupture (13) and failure at the interface epoxy/concrete or epoxy/FRP (32).

Even though there are more pullout tests available in the literature, the database used in this work consisted only in 75 specimens with similar parameters.

All the analysis and the prediction models obtained in this work used this database of pullout tests.

Table 2: Overview of the main parameters of the database used.

Parameter	Range
Concrete specimen shape	Parallelepiped and C-Shaped
Concrete strength [MPa]	from18.4 to 64.8
Bonded length [mm]	from 30 to 350
Groove size (width/depth) [mm]	from 3.2 / 12.0 to 24 / 25
Laminate geometry (thickness/width) [mm]	from 1.2 / 10.0 to 4.0 / 20.5
Bar diameter [mm]	from 8 to 13
FRP Young's Modulus [GPa]	from 100 to 182

4. RESULTS

The following sections present the main results obtained in the analytical analysis, both with the existent code formulations and with the DM algorithms. In all the analysis, mean values for the mechanical properties and no additional safety factor or strength reductions were considered.

4.1 NSM formulations

Figure 2 presents a comparison between the predictions for the NSM pullout strength of the 75 specimen's database using ACI and SA formulations. In order to simplify the analysis of the results, two lines were added to the charts marking the 20% variation line which is assumed as a reasonable value to take into account all the deviations that can exist in the available experimental data.

As it can be seen, the predictions are quite inaccurate, i.e., the results present large dispersion and many of them are outside the 20% lines, meaning that those results are either conservative or dangerous from the safe design point of view.

When comparing ACI and SA predictions with those from Equation (1) and MR, it can be pointed out that the dispersion is reduced since the dots in the charts related to these last models are closer to the 45º slope line. Despite this improvement, there are still many points remaining outside the 20% lines, even though closer than they were in ACI and SA predictions.

4.2 Data Mining

Figure 3 presents a comparison between the predictions for the NSM pullout strength of the 75 specimen's database using ANN and SVM formulations. This includes the information from both training and testing sets.

From these charts a clear improvement of the predictions pops up. A cloud of dots is concentrated in the 45º slope line (more clear in SVM case).

Nevertheless, there are still some points remaining outside the 20% lines. Worst, the points outside those lines, are mainly in the unsafe side.

As previously referred, DM algorithms not only export the output variable, which consists on the information presented in Figure 3, but also allows to export the weight of each input variable in the prediction of the phenomenon. As an example, for a few analyses, the average weights obtained from ANN and SVM are presented in Table 3. The main difference between the analyses shown is related to the number of inputs which were 8 and 7 for DM_8v and DM_7v, respectively. The other two analyses, DM_Eq1 and DM_best, use the variables presented in Equation (1) and the variables used in the best DM models, respectively. The input variables presented in this table were already defined with exception for k_b and k_d, which are the ratios between groove and FRP widths and depths, respectively.

From the analysis of this table, together with results from other analysis that are not presented in this paper, some interesting conclusions can be drawn: bonded length and FRP and groove perimeters are always the most influent variables; FRP modulus of elasticity and cross section area, when used in models where there are more than 3 inputs, seem to loose or even have no influence in the predictions, either separated or combined with each other; ratios k_b and k_d seem to have marginal influence; the best model (DM_best) was the one which presented more uniform influence of each input variable (all the three input variables had almost the same weight).

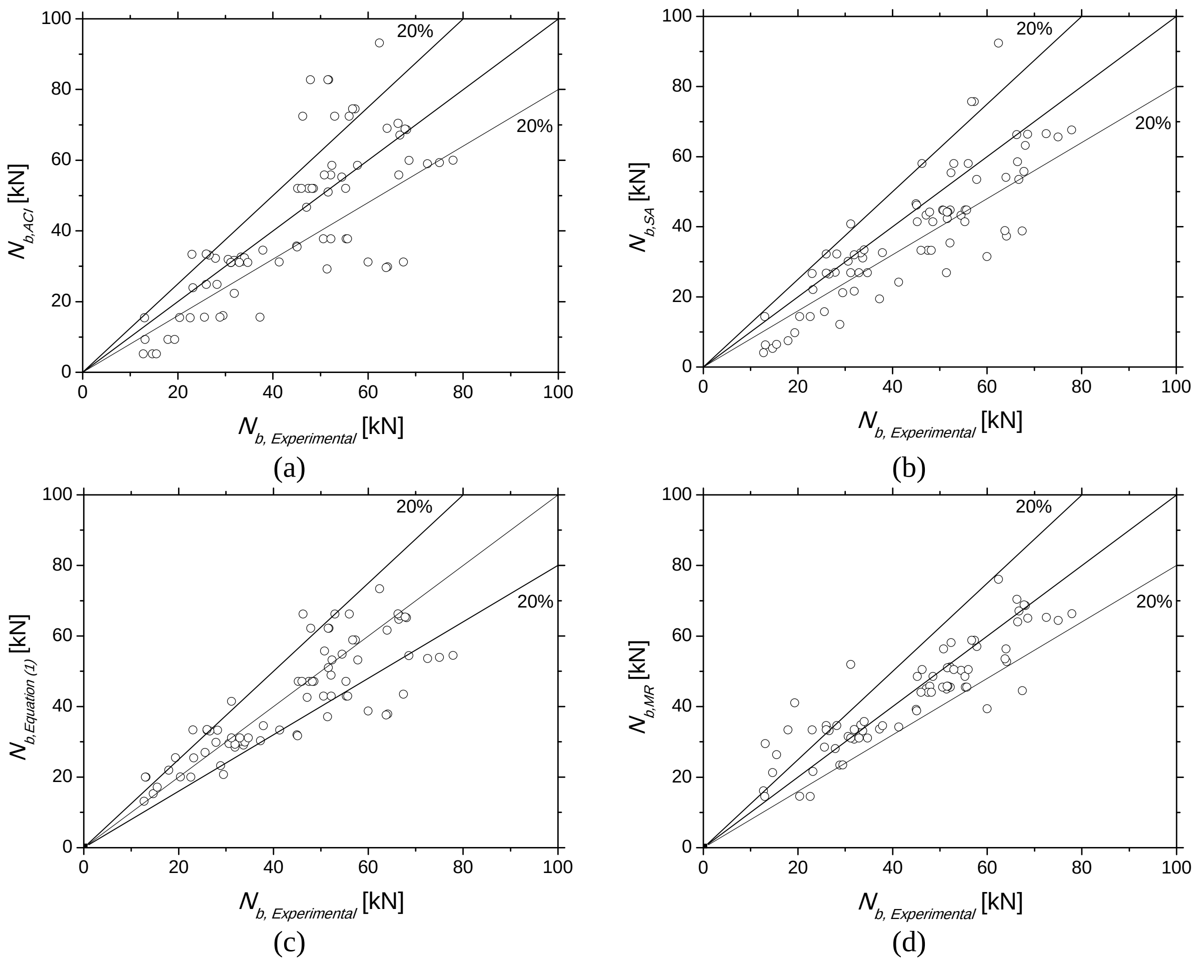
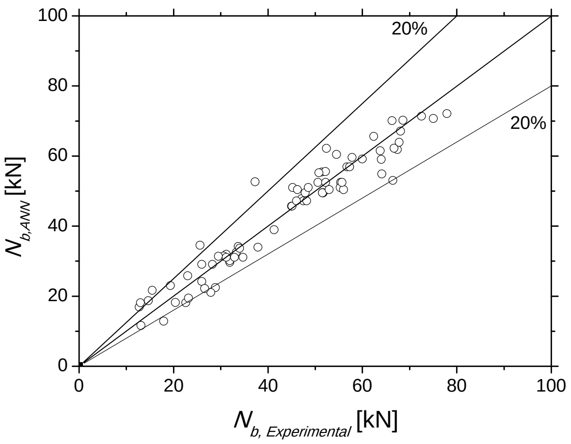
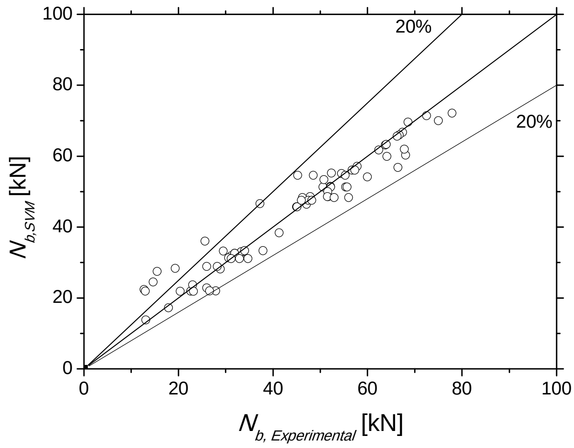


Figure 2: Experimental *versus* analytical prediction for NSM pullout strength of the 75 specimen's database using: (a) ACI; (b) SA; (c) Equation (1); (d) MR.



(a)



(b)

Figure 3: Experimental *versus* analytical prediction for NSM pullout strength of the 75 specimen's database using: (a) ANN; (b) SVM.

4.3 Analysis of the results

In order to correctly compare the results obtained by each formulation, some quantitative error measures were used in all analysis. These error measures were the mean absolute deviation (MAD) and the root-mean-squared error (RMSE), in addition to the traditional standard deviation (SD) and the coefficient of variation (CoV). Expressions (3) and (4) present MAD and RMSE definition where e_i is the error for the i^{th} specimen of the total N (difference between prediction and experimental).

$$MAD = \sum_{i=1}^{n} \left| e_i \right| \Big/ N \tag{3}$$

$$RMSE = \sqrt{\sum_{i=1}^{n} e_i^2 \Big/ N} \tag{4}$$

Table 3: Weights of input variables in some DM analyses.

Analysis ID	Input variables weight [%]									
	f_c	E_f	A_f	L_b	P_f	P_g	d_f	d_g	k_b	k_d
DM_8v	11.03	9.35	7.17	15.29	15.36	25.06			5.50	11.24
DM_7v	10.69	10.36*		19.25	16.34	19.97	8.10	15.29		
DM_Eq1				42.81	34.76	22.43				
DM_best	32.03	35.88*				32.09**				

*Input variable was the product E_fA_f; **Input variable was the product $L_bP_fP_gd_fd_g$.

Table 4 present a summary of those error measures for the six prediction models used in this work. In this table, minimum (Min.), average (Mean), maximum (Max.), standard deviation (SD) and coefficient of variation (CoV), are related to the ratio between models' predictions and experimental pullout strengths.

Table 4 reveals that, when looking from top to bottom, not only the error measures (MAD and RMSE) are successively lower but also dispersion measures (SD and CoV) too. In addition, the minimum and maximum values are getting closer to one.

To complement the analysis of the six models studied in this work, Figure 4 and 5 present the variation of the ratio between experimental pullout strength and the models' predictions with the variation of concrete strength and bonded length, respectively.

From this figures, it can be said that SA presented better performance (safer predictions) for concrete strengths lower than 40 MPa, while all other models behaved better for concrete strengths greater than 40 MPa.

In terms of bonded length, MR and Equation (1) present no tendency, while ANN and SVM are less safe for bonded lengths lower than 200 mm and ACI and SA for bonded lengths bigger than 200 mm.

These conclusions can be very useful from the design point of view since they provide an idea on the best model to use in each case. Since normally, in the case of structural strengthening of concrete structures, the bonded length is bigger than 200 mm and concrete strengths lower than 40 MPa, consider DM models can be a good option.

Table 4: Comparison between the results obtained in all the analyses performed.

Analysis	Min.	Mean	Max.	SD	CoV	MAD	RMSE
ACI	0.34	0.93	1.73	0.31	0.34	10.35	14.30
SA	0.32	0.85	1.48	0.24	0.28	9.03	11.56
Equation (1)	0.59	0.99	1.54	0.21	0.22	7.12	9.83
MR	0.64	1.04	2.25	0.29	0.28	5.88	7.88
ANN	0.72	1.01	1.41	0.12	0.12	3.37	4.40
SVM	0.79	1.04	1.77	0.19	0.18	3.03	4.37

5. CONCLUSIONS

This paper presented an analytical comparison between existing models to predict pullout strength of NSM CFRP systems and new models obtained by simple statistic analyses and by using DM algorithms.

The results revealed that improvements need to be made in the existent models since they present large dispersion. Results also reveal that simple statistic analyses can slightly improve the accuracy of the results and that DM algorithms can improve it even more.

The models obtained in all regression based works, like those presented in this paper, are influenced by the database used. The main difference from closed expression models and DM models is related to the number of experimental data used in each case. ACI and SA models were obtained with the databases of experimental results available until 2008. In this work, the database used had almost the same number of specimens but they are more uniform in terms of parameters involved. Additionally, regression based models should only be used when the same set of parameters is involved. These aspects can be easily overcome when using DM algorithms, if it is possible to do a few pullout tests representative of the new set of parameters and then add them to the existent database. In the future, as new results become available it would be interesting to reproduce this work in order to verify the main findings here obtained. Also, it will probably allow calibrate better the existing models.

Regarding DM, future and bigger databases should allow to clarify the apparently no influence of axial rigidity of the FRP in pullout strength and, even more important, should allow to give physical meaning to the variables that were used in the best DM models in order to add some rationality to these models. In this context, if new data allows, some other parameters should also be added to the analyses, namely, the distances from the loaded extremity of the bond zone to the top of the concrete specimen, from the centerline of the groove to the side edge of the specimen and between grooves (to analyze the interaction), when more than one exists. From the literature analyzed, it was found that some of these parameters aren't always provided.

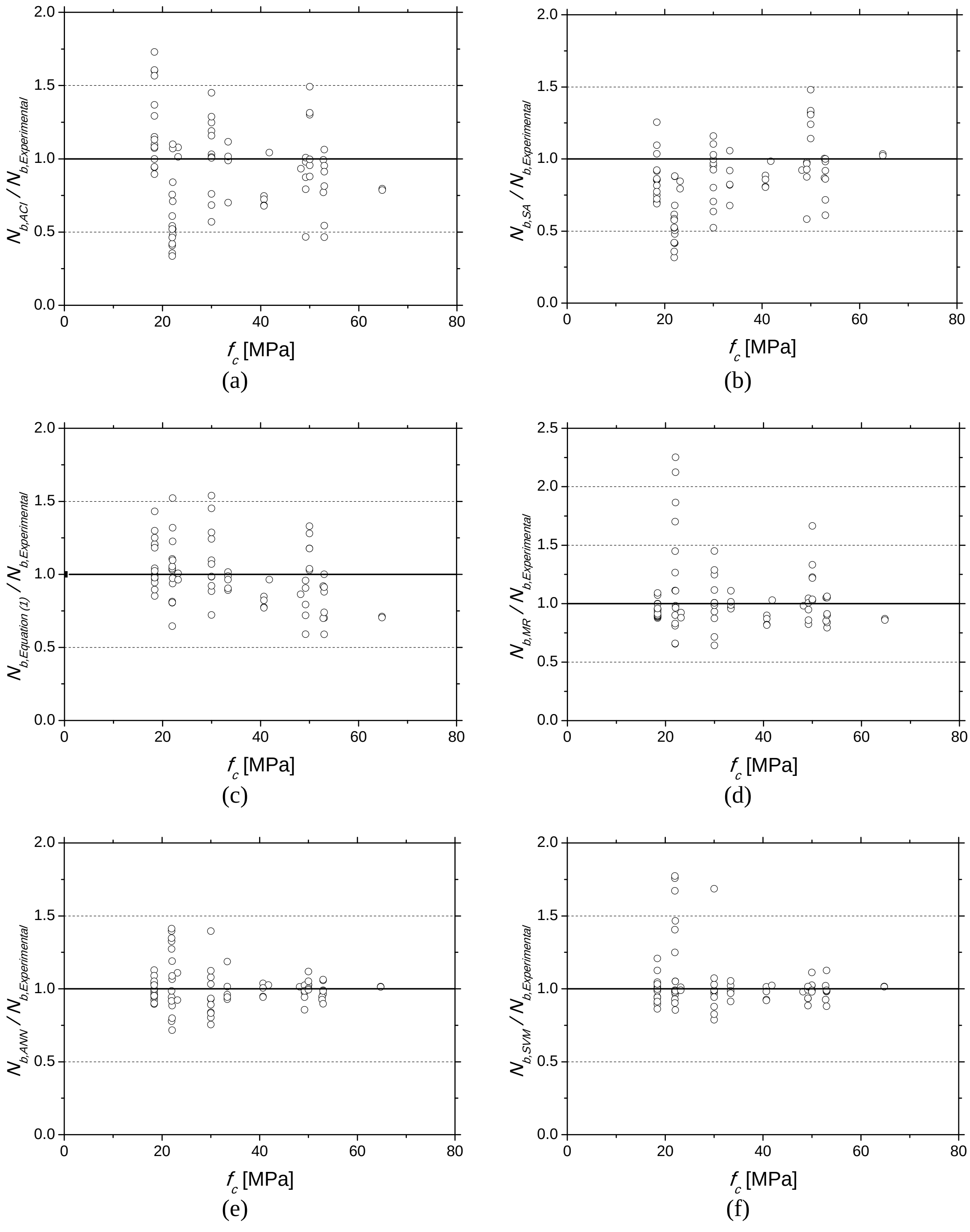


Figure 4: Variation with concrete strength of the ration between experimental pullout strength and the prediction using: (a) ACI; (b) SA; (c) Equation (1); (d) MR; (e) ANN; (f) SVM.

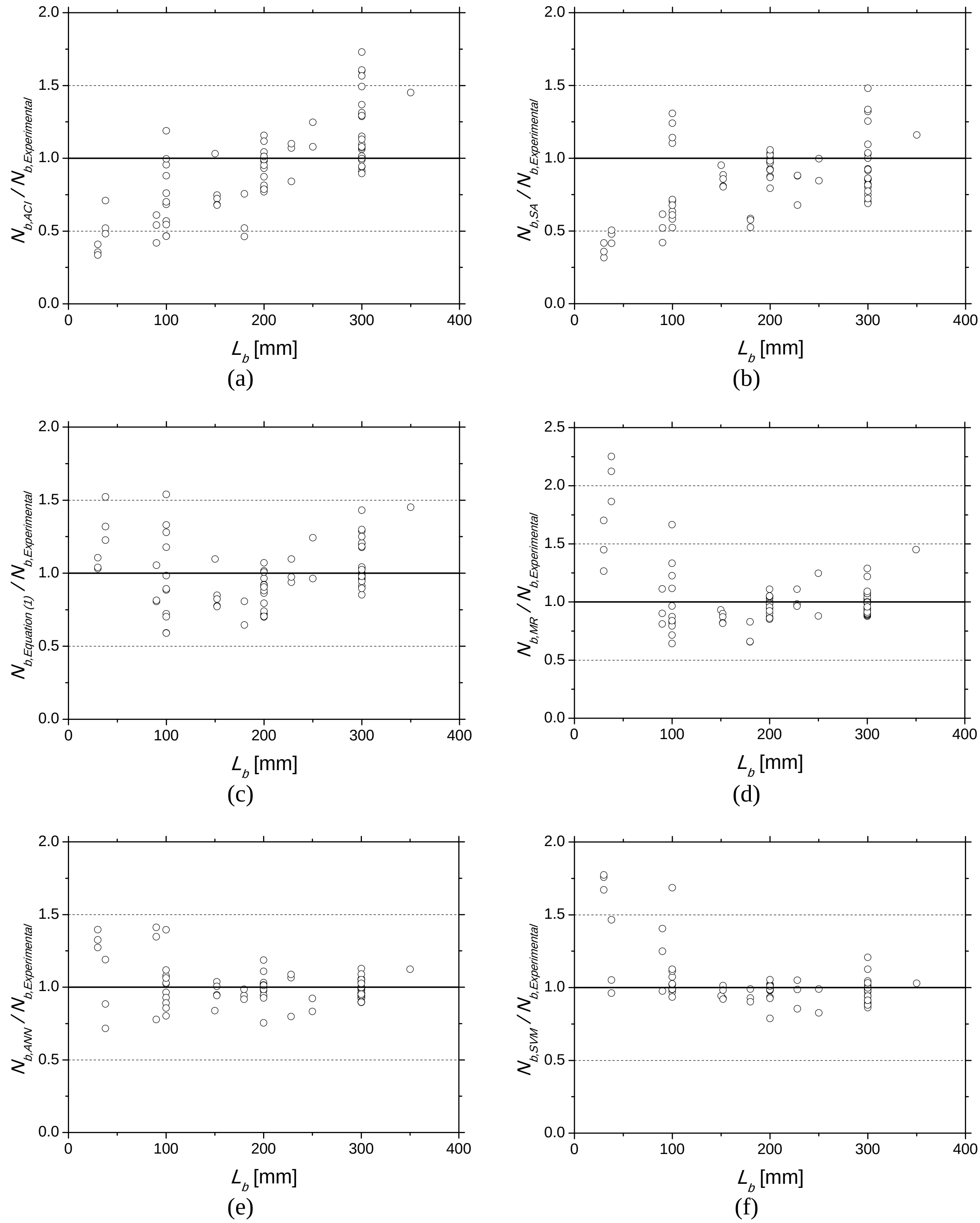


Figure 5: Variation with bonded length of the ration between experimental pullout strength and the prediction using: (a) ACI; (b) SA; (c) Expression (1); (d) MR; (e) ANN; (f) SVM.

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