Volume 10, Number 5 (October 2017) p. 1051 – 1074 • ISSN 1983-4195
http://dx.doi.org/10.1590/S1983-41952017000500007

REVISTA IBRACON DE ESTRUTURAS E MATERIAIS
IBRACON STRUCTURES AND MATERIALS JOURNAL

Artificial neural networks application to predict bond steel-concrete in pull-out tests

Aplicação de redes neurais artificiais na predição da aderência aço-concreto em ensaios do tipo pull-out

A. LORENZI [a]
alexandre.lorenzi@ufrgs.br

B. V. SILVA [a]
dovalesilva@hotmail.com

M. P. BARBOSA [b]
mbarbosa@dec.feis.unesp.br

L. C. P. SILVA FILHO [c]
lcarlos66@gmail.com

Abstract

This study aims the possibility of using the pull-out test results – bond tests steel-concrete, that has been successfully carried out by the research group APULOT since 2008 [1]. This research demonstrates that the correlation between bond stress and concrete compressive strength allows estimate concrete compressive strength. However to obtain adequate answers testing of bond steel-concrete is necessary to control the settings test. This paper aims to correlate the results of bond tests of type pull-out with its variables by using Artificial Neural Networks (ANN). Though an ANN is possible to correlate the known input data (age rupture, anchorage length, covering and compressive strength of concrete) with control parameters (bond stress steel-concrete). To generate the model it is necessary to train the neural network using a database with known input and output parameters. This allows estimating the correlation between the neurons in each layer. This paper shows the modeling of an ANN capable of performing a nonlinear approach to estimate the concrete compressive strength using the results of steel-concrete bond tests.

Keywords: bond steel-concrete, artificial neural networks, pull-out test, concrete strength, APULOT test.

Resumo

O estudo visa avaliar a possibilidade de se usar os resultados do ensaio de arrancamento “pull-out test” – ensaio de aderência aço-concreto para estimativa da resistência à compressão do concreto, este método vem sendo utilizado com sucesso pelo grupo de pesquisa APULOT, desde 2008 [1]. A pesquisa ora realizada evidencia a existência da correlação entre essas duas variáveis, aderência e resistência à compressão do concreto, o que permite determinar estimativas apropriadas da resistência à compressão do concreto, melhorando deste modo a capacidade do controle tecnológico “in situ” do concreto. Entretanto para se obter respostas adequadas dos ensaios de aderência aço-concreto é necessário controlar as configurações de ensaio, dado que existem diversos formatos de corpos de prova para estes tipos de ensaios na literatura. Deste modo, este trabalho tem por objetivo correlacionar os resultados obtidos em ensaios de aderência do tipo pull-out a suas variáveis por meio da utilização de Redes Neurais Artificiais (RNA). Com a utilização de uma RNA, pode-se correlacionar, de forma não linear, dados de entrada conhecidos (idade de ruptura, comprimento de ancoragem, cobrimento e resistência à compressão) com parâmetros de controle (tensão de aderência aço-concreto). Para gerar o modelo neural é necessário treinar a rede, expondo-a a uma série de dados com parâmetros de entrada e de saída conhecidos. Isto permite estimar os coeficientes de correlação entre os neurônios de cada camada. O presente trabalho apresenta a modelagem de uma RNA capaz de realizar uma aproximação não linear, visando estimar a resistência à compressão do concreto a partir dos resultados de ensaios de aderência aço-concreto.

Palavras-chave: aderência aço-concreto, redes neuriais artificiais, ensaio pull-out, resistência à compressão do concreto, ensaio APULOT.

[a] *Federal University of Rio Grande do Sul (UFRGS), Post-Graduation Program of Civil Engineering (PPGEC), Structural Models and Testing Laboratory (LEME), Porto Alegre – RS, Brazil;*
[b] *Federal University of São Paulo (UNESP), Department of Civil Engineering, Ilha Solteira/SP, Brazil;*
[c] *Federal University of Rio Grande do Sul (UFRGS), Post-Graduation Program of Civil Engineering (PPGEC), Structural Models and Testing Laboratory (LEME), Porto Alegre/RS, Brazil.*

Received: 18 Jun 2016 • Accepted: 25 Apr 2017 • Available Online: 04 Oct 2017

1. Introdução

The use of Artificial Intelligence (AI), which enables the development of templates to aid in the diagnosis and decision-making. There are several modeling techniques of data and production of information that seek to simulate human intelligence, fundamental strategy to enable them to solve complex problems, such as Hypothesis Testing, Nebula Logic, Expert Systems, Artificial Neural Networks, among others. One of the most promising techniques of AI uses Artificial Neural Networks (ANNs). It is a suggested method to solve complex problems, based on the construction of a computational template made of circuits that simulate the functioning of the human brain. This is the case of the interpretation of results of a pull-out steel-concrete bond test, which demands special knowledge and can be simulated using these tools.

Throughout the use of ANNs, it is possible to correlate, in a non-linear way, known input parameters, such as age, length of anchoring, spreading and compressive strength with desired control parameters, as the tension of steel-concrete bond, as an output to neural model.

The ANNs can be generated using multiple layers' perceptron (MLP) and trained with an error back propagation algorithm, for example, the ones that are submitted to a big number of input and output data, allowing it to make an appropriate estimate of the correlation coefficients in each layer.

The research group LEME (Structural Models and Testing Laboratory) has sought in recent years to implement features to improve the analysis of reinforced concrete structures. The work developed by LORENZI (2009) [2] showed that the ANNs can be used to generate numerical methods possibly applicable for estimation of compressive strength from tests of propagation of ultrasonic pulse velocity (UPV). The research group APULOT has been working hard in studies to check the possibility of using the results of the testing of bond steel-concrete for estimating compressive strength of concrete. The authors Silva (2010) [3]; Lorrain et al. (2011) [4] show that the correlation between these variables is valid and it is possible to make appropriate estimates of compressive strength. However, to get appropriate responses of steel-concrete bond tests it is necessary to control the settings, considering, among other parameters, the existence of various shapes of specimens for these types of tests.

Processing various data can be a complex task and demand a lot of time. Among the existing numerical methods of data processing, the ANNs, which bills itself as a proposed numerical method to solve problems, determines the correlation between the compressive strength of concrete and bond stress of steel-concrete on certain tests.

In this work, the results of some studies developed by the group of researchers LEME/APULOT are presented. They are aimed to the modeling of an ANN if it is efficient to represent the non-linear relation between a dataset of compressive strength and steel-concrete bond stress.

In this way, the aim of this study is to evaluate the potential of ANNs for interpretation of data to present the modeling of an ANN able to perform a non-linear approach. It focuses to estimate compressive strength of concrete from the results of the testing of steel-concrete bond and to demonstrate the accuracy of the estimate of the ANNs in front of multiple regression statistical models.

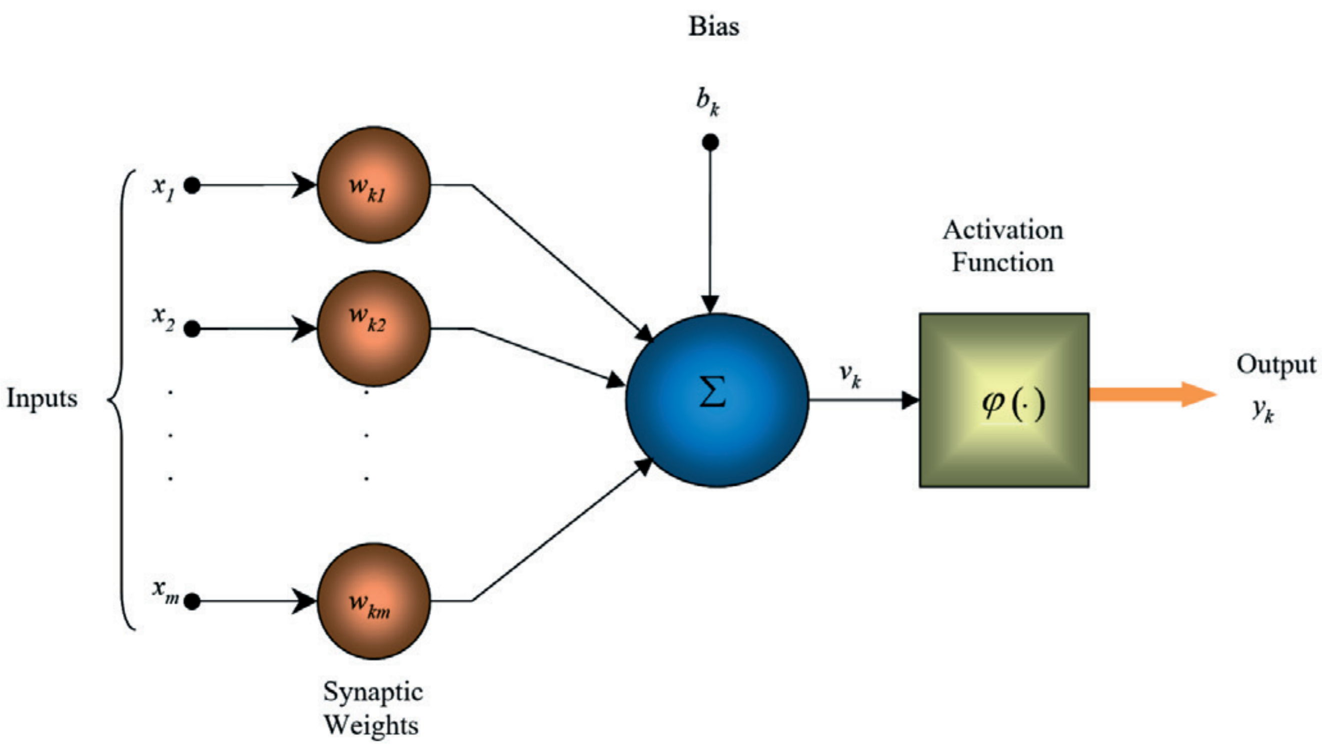

Figure 1
Model of non-linear neuron [6]

2. Artificial Neural Networks

How SRIRAM (1997) [5] explains, the ANNs are computational techniques that generate models inspired by the neural structure of intelligent organisms and acquire knowledge through analysis of previous experiences. In its most general form, ANN is a structure designed to work similarly to how the brain performs a certain task of interest. To achieve a good performance, the ANNs adopt a strategy of massive interconnection of simple computational cells, called neurons, or processing units (HAYKIN, 2001) [6].
ANNs are a different computer system from the conventional paradigm, which is based on a central processor element controlling the system. The neural paradigm processing is done through distributed artificial neurons. The elements of the ANNs processors operate in a parallel way, interacting with each other. The network learns to solve a task that is assigned through a training algorithm. The operation of the model depends on the dynamics of neurons and how they are connected, which will determine the type of task that will be performed over the network. As networks are based on an analogy of functioning of the brain, next item discusses, briefly, some aspects related to the way it operates. (CORRÊA, 2004 [7]).
The functioning of ANNs is based on the relation established between stimuli input and output of a system, and have the advantage that, for this purpose, it is not necessary to establish a previous mathematical model that defines the forms of these relations. The networks learn these relations of the data themselves, from a training process, similar to the learning of the human brain.
The network structure resembles the brain in two aspects: the knowledge is acquired by the network from records of the entry and exit conditions of any proceedings, through a learning process, which can be driven or stand-alone. Synaptic weights, which represent the connection strengths between neurons that form the network, are used to store learned knowledge.
A typical network consists of an input layer, composed of as many neurons as it is necessary to encode the information; one or more hidden layers, which allow the transformation of information according to a structure of weights that was established when the network was trained; and an output layer, which records the result of the processing performed. Each unit or neuron saves only one value that changes depending on the stimuli received from all neurons that precede and are linked.
Figure 1 illustrates the basic operation of a neuron. As shown in the figure, the neuron receives a series of input signals or stimuli, each activated with a specific weight. The stimuli are combined through an additive function, which can be influenced by a trend (or bias) introduced in the system. The result is filtered by an activation function. This generates an output signal with a certain intensity, which will serve as a stimulus for the next neuron.
The relation between neurons are called connections and are characterized by having different intensities. These intensities are represented by the synaptic weights, which are existing correlation coefficients between neurons. An ANN works through the dissemination of stimuli between its layers, while the array of synaptic weights modifies these stimuli, generating different responses to different stimuli.

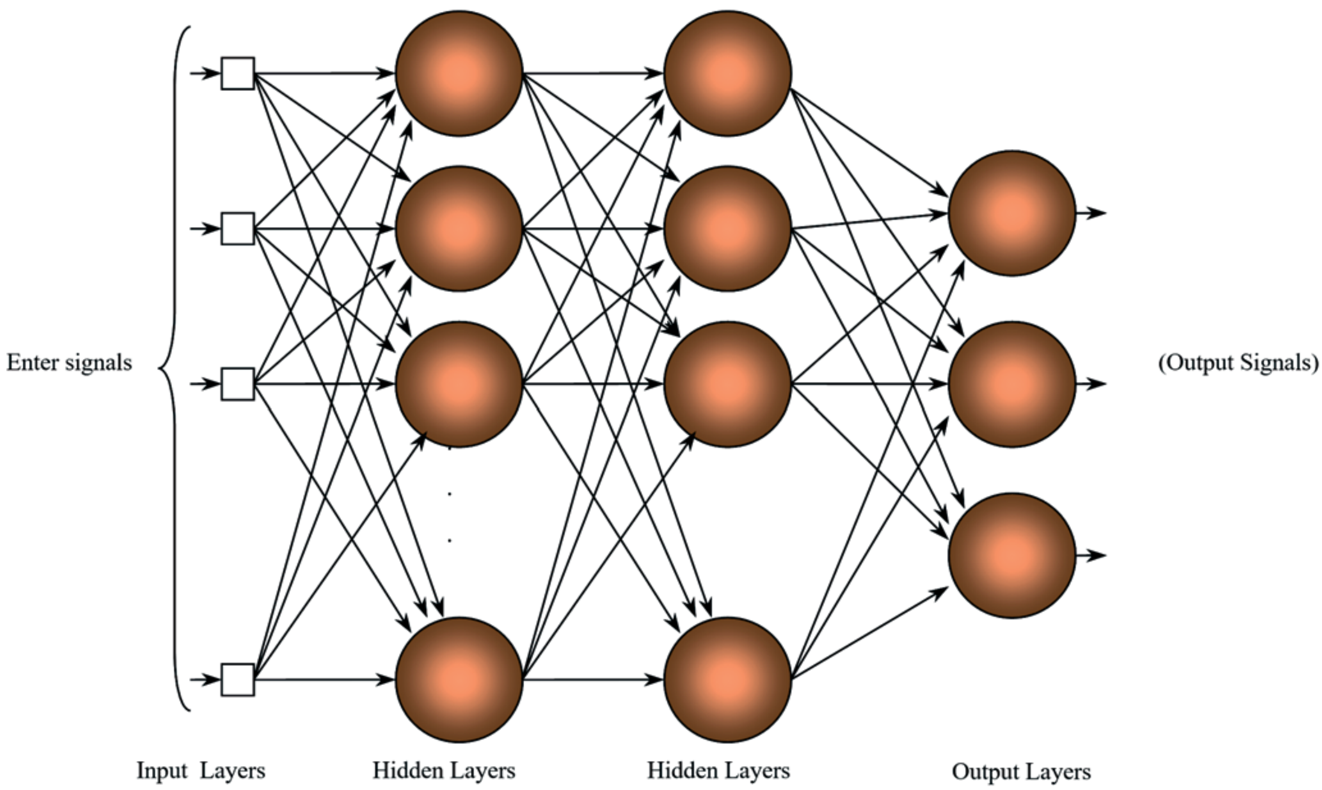

Figure 2
Representation of an ANN with two hidden layers [6]

To implement ANN, it is used networks of neurons that are structures able to represent more complex surfaces. The use of a set of well-articulated neurons allows the network “reason,” establishing a non-linear relation between stimulus and result. This structure allows the known multilayer perceptron (MLP). Figure 2 shows a schematic model of a perceptron of 4 layers, which contains two hidden intermediate layers.
According to Haykin (2001) [6], the training is supervised using an Error Back Propagation algorithm - EBP. This algorithm is based on the use of interaction, changing synaptic weights, backward, seeking to reduce the error at the end of the training. The same involves two steps: the propagation and back-propagation. During propagation, a vector of input is applied to sensory network nodes and its effect is multiplied through the network, to produce a set of stimuli, output that characterize the response from the network.
Comparing the response generated with the expected, it’s checked if it is necessary to adjust the synaptic weights. This occurs during back-propagation, in which synaptic weights are adjusted according to a rule of error correction. The synaptic weight adjustment causes the actual response of the network moves closer to the desired response, in a statistical sense.
One of the most important properties of ANNs is the ability to simulate the learning, that is, to use new data to adjust the model and improve performance. Learning is a process by which the free parameters of ANN are adjusted, through a process of stimulation, the environment in which it is inserted. Depending on the way the modification of parameters occurs it is determined which is the learning strategy (HAYKIN, 2001) [6].

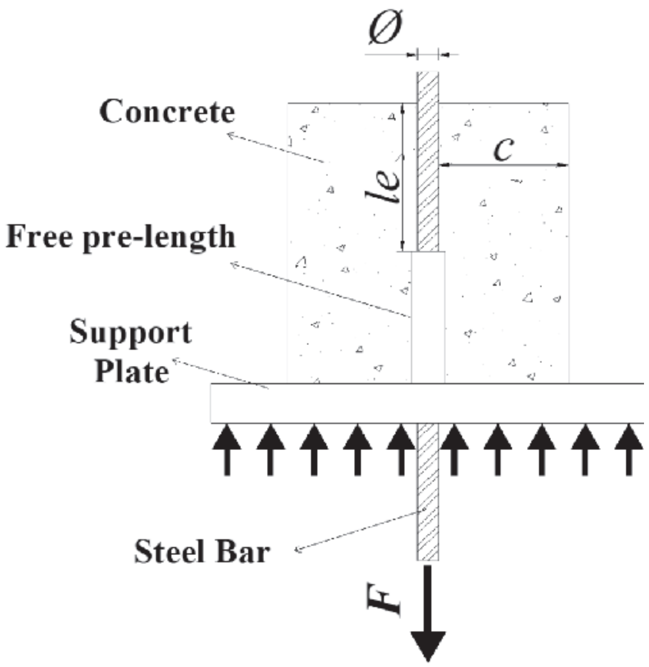

Figure 3
Scheme of pull-out test showing ANN control variables

3. Estimation of the bond stress steel-concrete from pull-out tests

The bond between steel and concrete is a determinant factor for the good behavior of reinforced concrete structural. The FIB (2000) [8] stresses that the knowledge of the behavior of the bond is essential for the correct understanding of the rules to calculate the length of anchoring and amendments by armor bars crossover, for the calculation of displacements considering the stiffening effect by traction control, cracking and the minimum amount of armor. There are several factors that influence in adherence steel-concrete. ACI 408R/2003 [9] emphasizes the following: type of ribbed bar configuration, the diameter of the bar, the situation of the bar’s surface (deterioration), the layout of the bar at the time of the launch of concrete (horizontal or vertical), the water-cement ratio (w/c), the mechanical strength of concrete, mineral additions, as well as the pozzolanic materials, the physicochemical characteristics of materials used in concrete, the density and age, among others.
There are several test methods described in the literature (FIB, 2000) [8], to measure the steel-concrete bond. The most used are the pull-out test (pull-out test) suggested by the technical recommendation of RILEM CEB/FIP/83 [10]. With the completion of the test, which schema is shown in Figure 3, it is possible to get the intensities of the forces in kilonewtons in function of the offset. With this value of force divided by the area of the bar anchoring the bond stress (τb), as shown in Equation 1. In this equation «F» is the force of pullout, «Ø» is the diameter of the steel bar, «le» is the anchoring length of the test and «c» is the concrete coverings. It is noteworthy that the maximum bond stress (τb, max) is calculated based on the maximum pullout force obtained in the tests.

$$\tau_b = \frac{F}{\pi \emptyset le} \quad (1)$$

Many variables, as described above affects the results of maximum bond stress. To improve the efficiency of the method it is necessary to develop more sophisticated models, which is the subject of ongoing research. Given the synergy effects and lack of knowledge about each one of them, it is possible to say that this is a problem that requires a non-linear modeling of unstructured knowledge, which justifies the use of modeling technique via ANNs.

4. Model

To achieve the objective proposed for this work, it is used ANN with four layers, implemented with the use of the software MATLAB 6.0, suitable for interpretation of data from tests of steel-concrete bond, to produce estimates of concrete compressive strength.
It was settled the number of layers in 4 because of the initial number of samples of this database at the beginning. For the database used (562 samples) it is considered that this amount of correlations allows us to provide a good flexibility and interpretation capacity to the network, as preliminary studies conducted by the research group LEME [11], [12], [13] and [14]. In these studies, it is concluded that this type of network can produce an adequate simulation and consistent with the objective of the research. The input data were normalized using for this purpose the function *premnmx*, which pre-processes the network training through the normalization of entries and targets within the range [-1 1].

To analyze how the structure of the network affects the accuracy of performance, the characteristics of the network standard were modified, being varied the number of neurons and the control parameters, to find out how these changes affected the result.
The source data used in this study to train and test the ANNs encompassed results of tests of steel-concrete bond of pull-out tests, in three different searches. Table 1 shows the data removed and its authors.
The data used in this study to train and test the ANNs encompassed results of pull-out tests, with the maximum bond stress between values of 4.0 to 50.2 MPa. Figure 4 shows the distribution of the data used (steel bar diameter Ø x compressive strength "fc" x bond stress "τb"). Figure 5 shows the number of observations in each maximum bond stress range for the results used to form ANN.

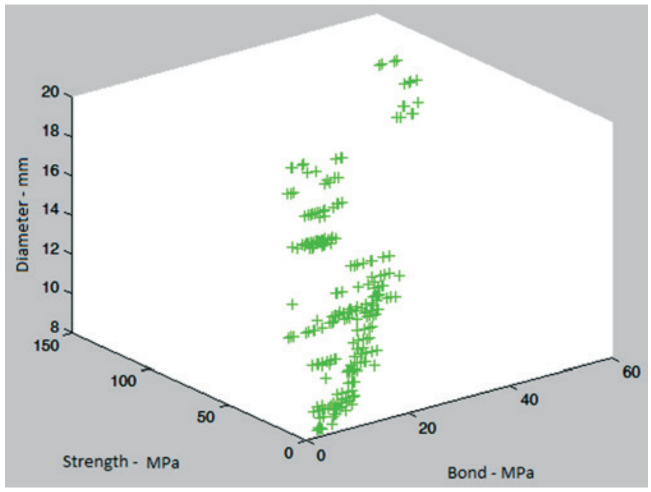

Figure 4
Distribution of bond tests data pull-out, used to compose ANNvariables

Table 1
Experimental data

References	Ø (mm)	le (mm)	c (mm)	Age (days)	Concrete compressive strength f_c (MPa)
Castro (2000) [16]	16	80	52 / 92	15 / 18	83,04 / 86,14
Fernandes (2000) [17]	10 / 20	50 / 100	45 / 90	28	27,47 / 27,99
Barbosa (2002) [18]	16 / 20	80 / 100	52 / 90	90	33,63/54,77/63,31/
França (2004) [19]	16	80	92	28 / 90	32,97 / 35,21
Almeida Filho (2006) [20]	10 / 16	50 / 80	45 / 72	7 / 14	30 / 60
Graeff (2007) [21]	8/12,5	40/62,5	36/56,2	21	25
Caetano (2008) [15]	12,5	62,5	61,8	63	25 / 45 / 65
Simplício (2008)[22]	6,3/8/10/ 12,5/16	18,9/24/30/ 37,5/48	96,9/96/95/ 93,8/92	90	40/35,9/41,4/34/37,4/39,4 /40/39,6/28/29,1/29,3
Reis (2009)[23]	10/16	50/80	45/72	28	23,6/ 37,2
Silva (2010) [3]; Silva et al. (2013) [24]	8/10 /12,5	40/50/62,5	96/95/93,7	3/7/28	16,7/21,1/28/33,1/40,5/49,9
Lorrain et al. (2010) [25]	12,5	62,5	56,2	28	20
Lorrain et al. (2011) [4]	8	80/135	36	3/7/14	6,8/8,1/15,07/23,54/26,75/ 27,12
Ferreira et al. (2011)[26]	6,3/8/10	31,5/40/50	46	7	38,2/45,3
Tojal (2011)[27]	10/16	50/ 80	45/ 72	28	34,5
Silva Filho et al. (2012) [28]	12,5	62,5	56,2	28	27,4
França (2012)[29]	6,3/8/10	31,5/40/50	96,9/96/95	21	25/40
Baiochi et al. (2013) [30] Jacintho et al. (2013)[31]	10	63	46	7/28	49,56/59,63
Godoy et al. 2012)[32] Jacintho et al. (2014)[33]	8	110	46	14/ 28	23,54/38,27/43,27
Lovera e Frutos (2013)[34] Gavilan et al. (2014)[35]	8	91/80/70/63	46	3/5/7/28	20/25/30/35
Silva (2010) [3]; Silva et al. (2014)[36]	8/10/12,5	80/100/125/ 48/60/45	46/45/43,75	3/7/28	16,7/21,1/28/33,1/40,5/49,9
Martins et al. (2014)[37]	8	95/47/39,6	45	7	23,15/45,40/50,61

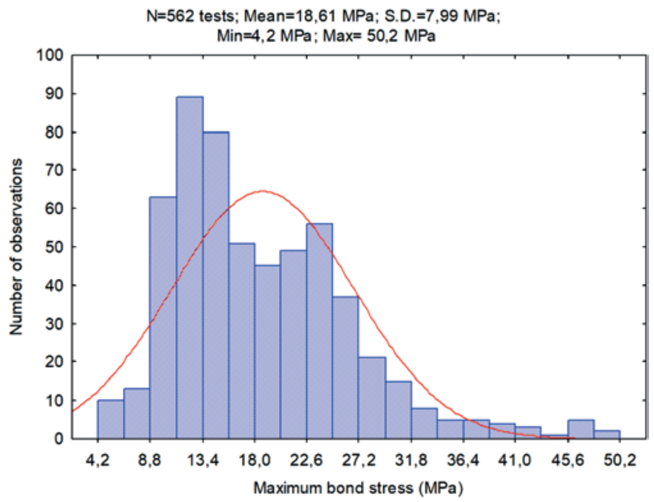

Figure 5
Distribution of the results of maximum bond stress used in ANN

Figure 6 shows the direct relation between compressive strength and maximum bond stress, evidencing an R^2 equal to 0.5821.
The relation between the data was estimated using multiple configurations of an ANN, trained with an error back propagation algorithm. It was controlled the estimation error and the number of training moments (steps of interaction), and registered the computational time spent to proceed with this train. To accomplish the approach it was used the format suggested by Caetano (2008) [15], shown in equation 2 :

$$\tau_{b,\text{máx}} = 10{,}34 \times \frac{1}{En^{0,5}} \times Ner^{0,25} \times fc_c^{0,5} \times \frac{1}{Te_c^{fc_c^{0,5}}} \times \frac{1}{Ø_c^{fc_c^{0,5}}} \times \left(\frac{0{,}3 + GC_c}{0{,}3 + GC_c^{1,4}}\right) \quad (2)$$

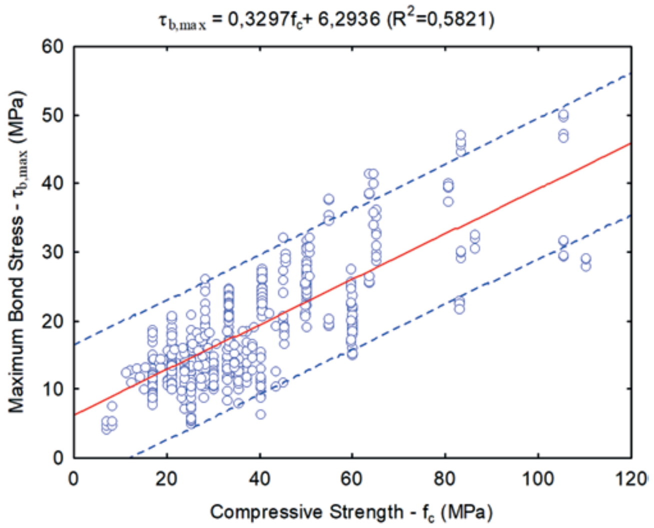

Figure 6
Relation between compressive strength and maximum adherence of pull-out tests used to compose the ANN

Where:
$\tau_{b,máx}$ = maximum bond stress in MPa. En = type of test (0.5 for simple pullout; 1,5 for eccentric pullout). Ner = type of rib (0.5 for 'N' type; 1.5 for 'n' type). fcc = encoded concrete's compressive strength, in MPa; $fc_c = \frac{fc}{30}$. Tec = encoded exposure temperature, in °C; $Te_c = 1$, for $Te \leq 350°C$. $Ø_c$ = steel bar diameter, in mm. $Ø_c = \frac{Ø}{16}$; GCC = degree of corrosion, encoded in percentage; $GC_c = \frac{GC}{2}$.

5. Results and discussions

All the data taken from the literature were with En = 0.5; NER = 0.5, room temperature, in other words, without high temperatures and no degree of corrosion.
Figure 7 illustrates the Neural Network Matlab Training Toolbox that was used to carry out the simulations through the *software* Matlab R2012.
Figures 8, 9 and 10 illustrate three of training simulations used for modeling the results obtained experimentally, to estimate the

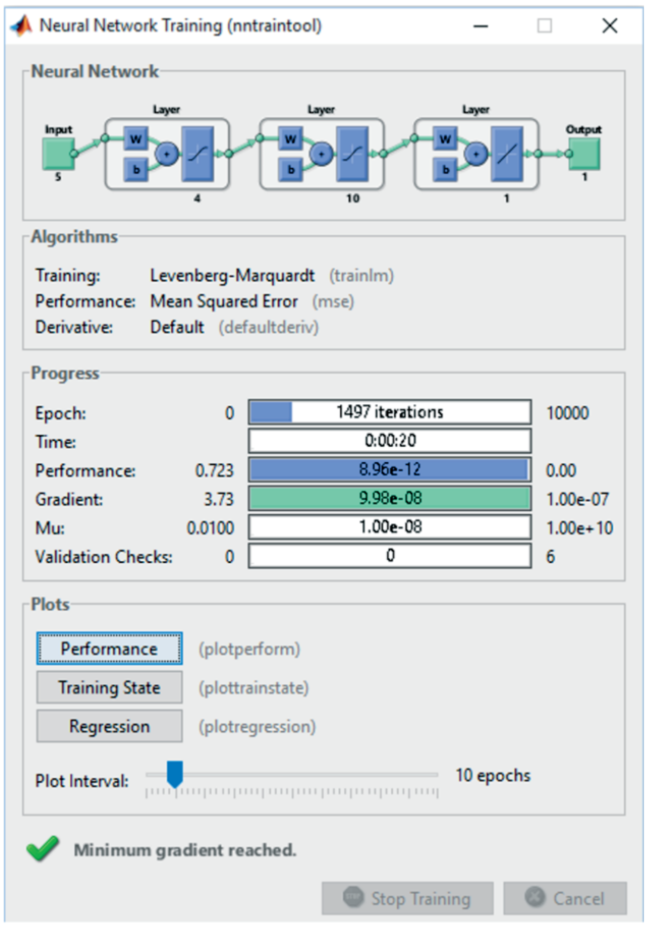

Figure 7
Matlab Neural Network Training Toolbox

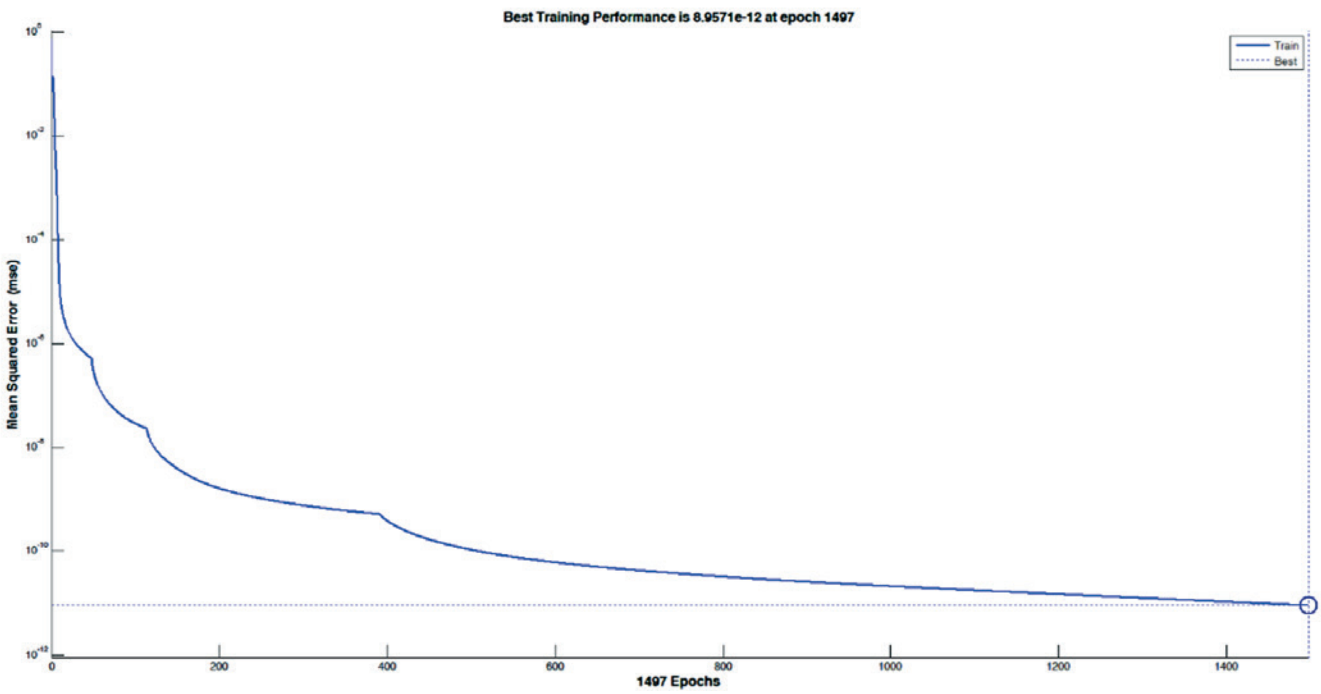

Figure 8
Evolution of Artificial Neural Network training - ANN 20x40x40x1

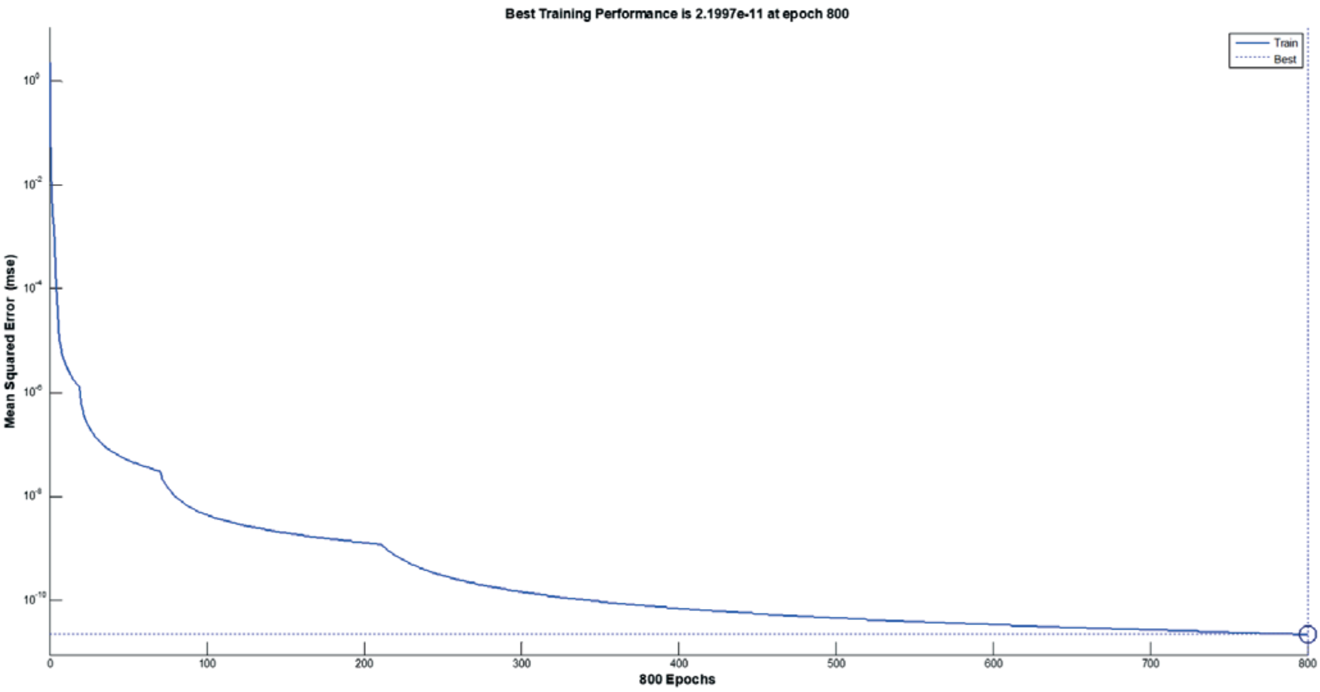

Figure 9
Evolution of Artificial Neural Network training - ANN 10x30x30x1

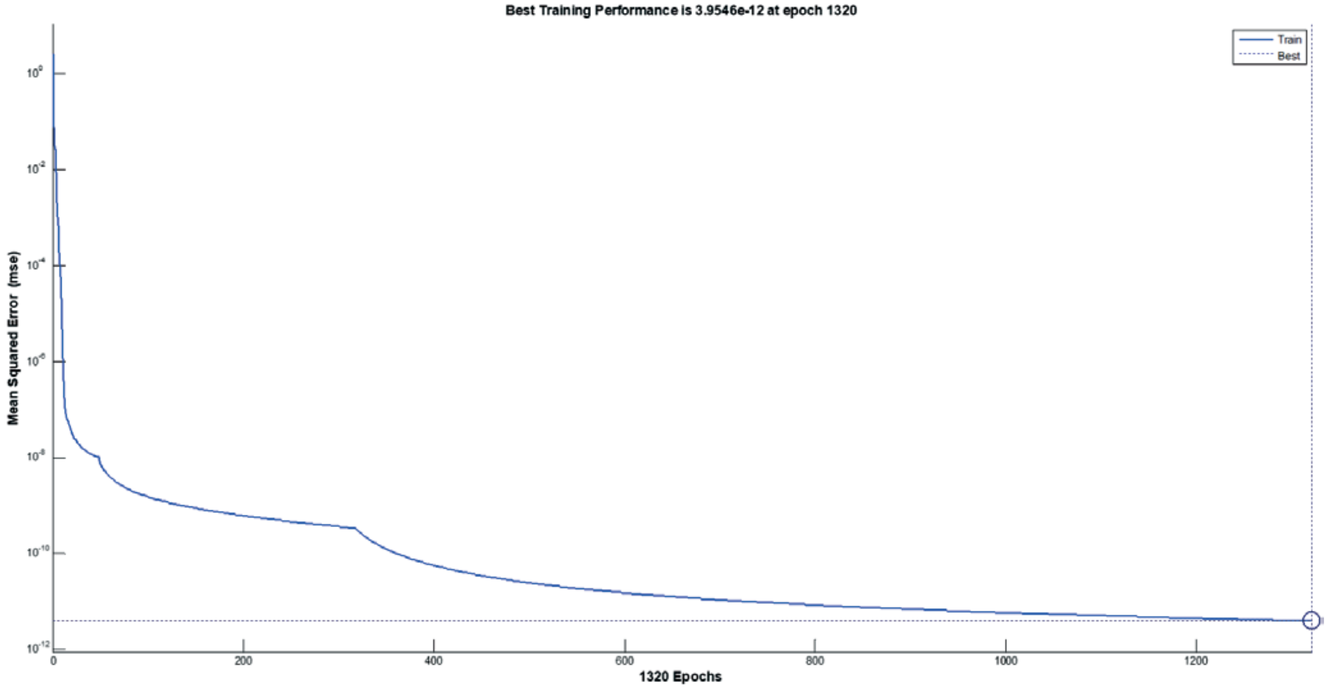

Figure 10
Evolution of Artificial Neural Network training - ANN 10x40x80x1

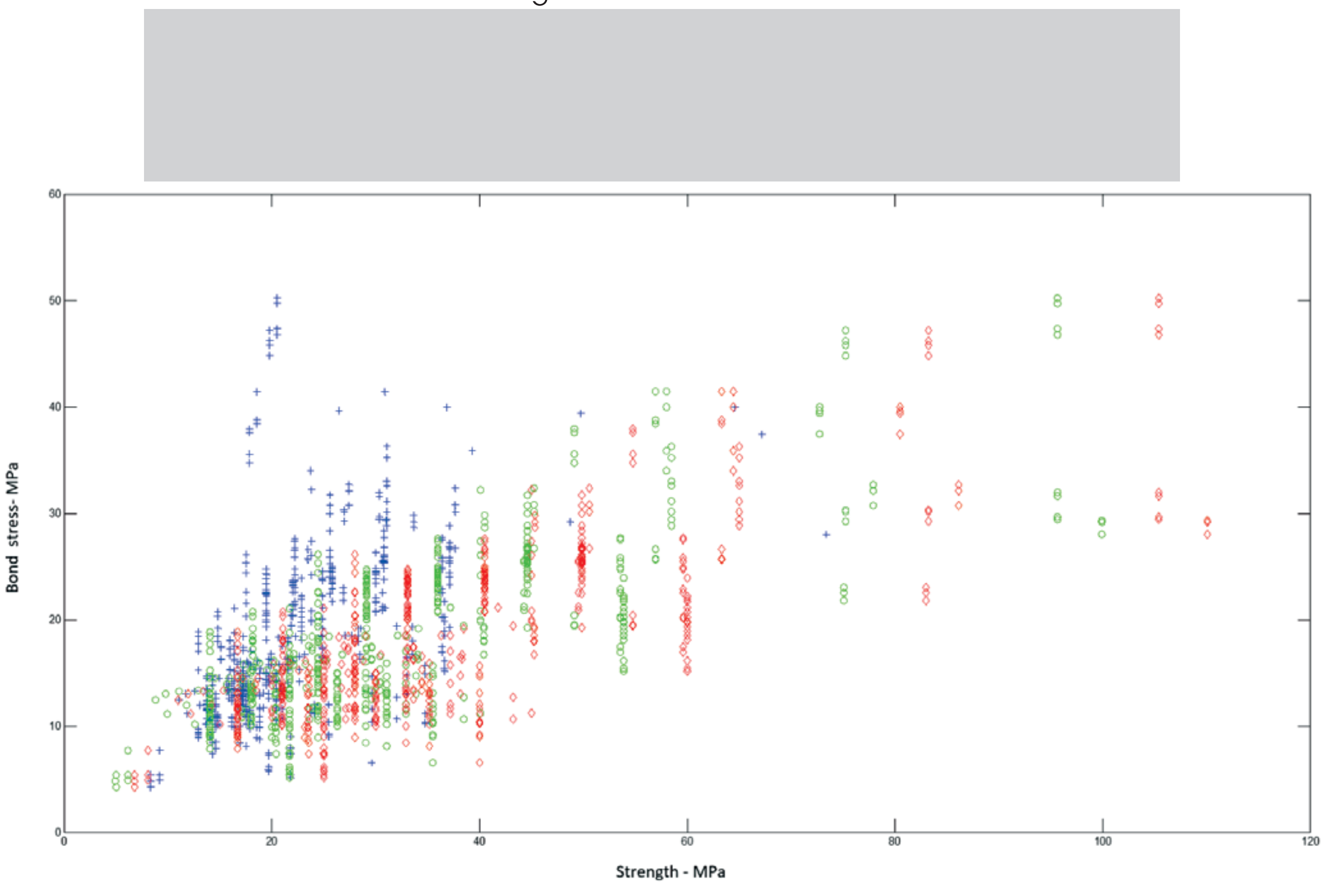

Figure 11
Artificial Neural Network modeling - ANN 20x40x40x1

compressive strength of concrete from the results of the testing of steel-concrete bond using ANNs. The line in blue represents the calculated error at each step of the network. By seeking the maximum training as possible, the allowable value for error average established for the network was zero.

Figures 11, 12 and 13 illustrate the results of three of ANNs that were tested in this study. Both simulations generated similar results. As it can be seen in those figures, the obtained results indicate that the power estimated from ANNs is effective. In those figures, the original data of 200 cases (red diamond), an estimate based on traditional statistical processes (blue cross) and the results of ANN (green circle) are represented.

Figure 11 shows the result obtained with the best perceptron studied, which had 20 neurons in the second layer, 40 in the third layer, 40 in the fourth and 1 in the output layer. In the first, the function of transfer used was the hyperbolic tangent sigmoid, while in the output layer the function adopted was linear.

Figure 12 shows the result obtained with the best perceptron studied, which had ten neurons in the second layer, 30 in the third layer, 30 in the fourth and 1 in the output layer. In the first, the function of transfer used was the hyperbolic tangent sigmoid, while in the output layer the function adopted was linear.

Figure 13 shows the result obtained with the perceptron studied, which had ten neurons in the second layer, 80 in the third layer, 80 in the fourth and one layer in the output layer. In the first, the function of transfer used was the hyperbolic tangent sigmoid, while in the output layer the function adopted was linear.

Although this study database is still small, it can be observed that, throughout the use of ANNs, the data obtained in experiments in relation to traditional statistical templates can be better adjusted.

Based on these first experiments, the permanence of this search will focus on increasing the database used in the simulation and use other training algorithms to performe this simulation.

6. Conclusions

This work sought to evaluate the possibility of using the steel-concrete bond tests to estimate the compressive strength of concrete (fc), a complicated initiative given the fact that the concrete is a very heterogeneous material and that changed through time.

The results show that it is possible to perform a non-linear mapping of the relation between the compressive strength of concrete x bond stress steel/concrete, considering parameters such as the length of the diameter of the bar anchoring, the age of rupture and the spreading of concrete around the steel bar (confinement). The news consisted in the employment of neural templates. Given the synergy of effects and lack of knowledge about each of the parameters that affect the estimation of the “fc,” it can be concluded that the problem requires a non-linear modeling of unstructured knowledge.

The modeling technique using ANNs presented itself as an effective tool for the treatment of the data proposed, given the ability of learning and generalization of acquired knowledge of ANN. However, it must be used a database that contains a significant amount of previous results, with a good variation of the parameters considered important for the assessment of the performance of the structure.

From the analysis of the results obtained, it can be inferred that the use of ANNs has the potential to produce robust and flexible numerical methods for interpretation of the testing of bond stress steel/concrete.

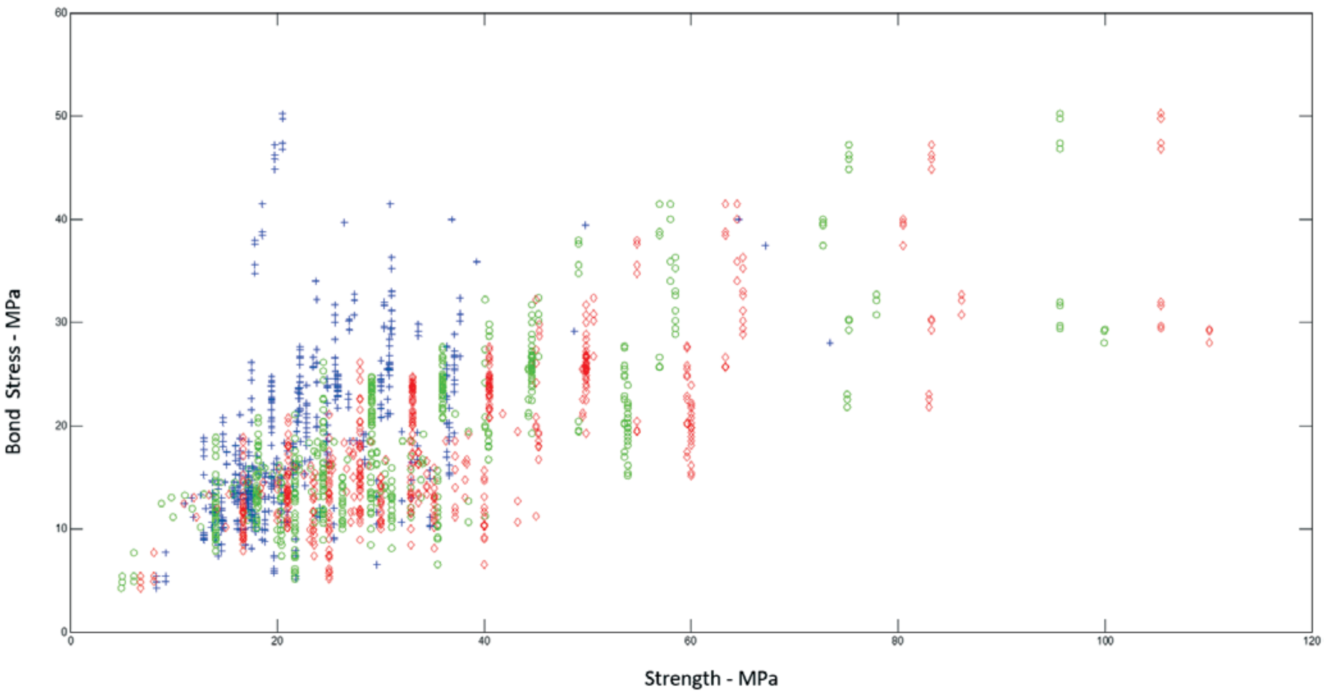

Figure 12
Artificial Neural Network modeling - ANN 10x30x30x1

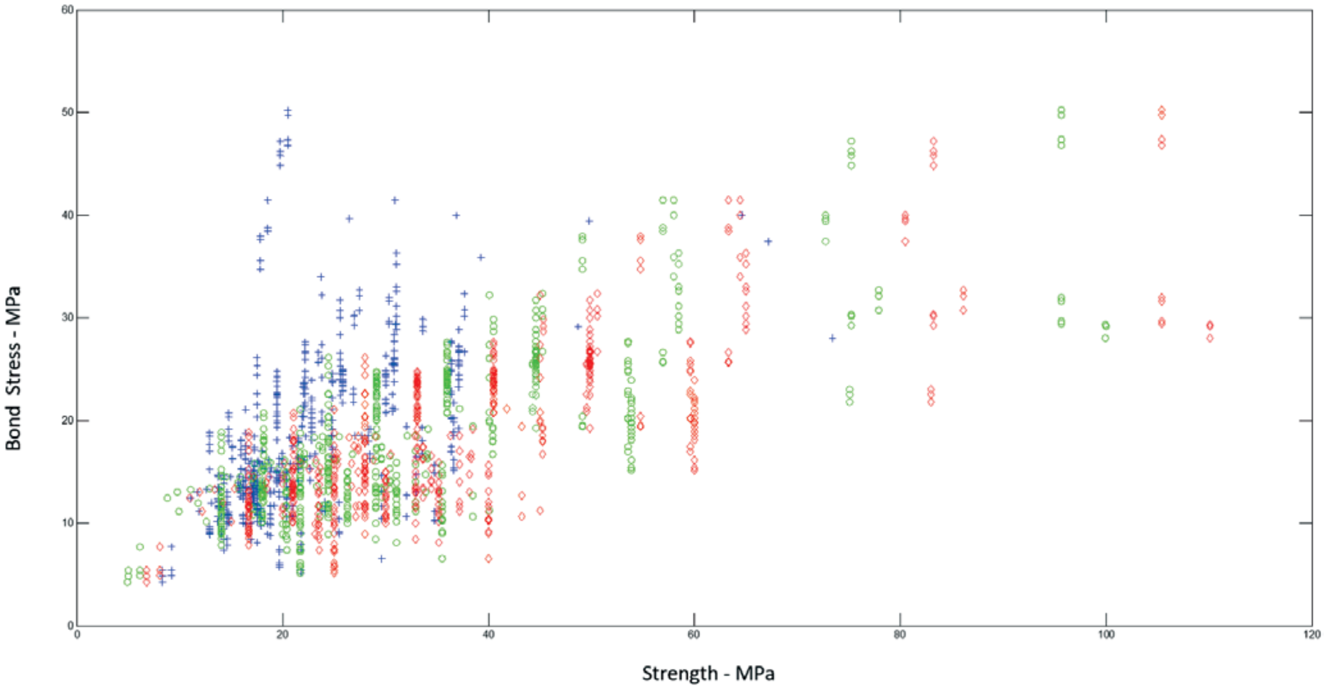

Figure 13
Artificial Neural Network modeling - ANN 10x40x80x1

These tests reinforce the idea that the use of the trial could be useful in the analysis of structures, confirming the idea that this test has great potential for use in the case of inspection of structures. The templates generated can be considered as dynamic as the networks can be improved when new data are collected. The results obtained indicate that ANNs has the potential to be used to obtain estimates of the compressive strength from data of bond stress steel/concrete, for inspection of structures.

7. References

[1] LORRAIN, M. S.; BARBOSA P. M. Controle de qualidade dos concretos estruturais: ensaio de aderência aço-concreto. In: Revista Concreto & Construções, São Paulo, Nº51, 3º trimestre, p. 52-57, 2008.

[2] LORENZI, A. Aplicação de redes neurais artificiais para estimativa da resistência à compressão do concreto a partir da velocidade de propagação do pulso ultra-sônico. Tese (Doutorado em Engenharia Civil) - Programa de Pós-Graduação em Engenharia Civil, Universidade Federal do Rio Grande do Sul, Porto Alegre, 2009.

[3] SILVA, B. V. Investigação do potencial dos ensaios APULOT e pull-out para estimativa da resistência a compressão do concreto. Dissertação (Mestrado em Engenharia) - Faculdade de Engenharia de Ilha Solteira, Universidade Estadual Paulista, UNESP, 2010.

[4] LORRAIN, M. S. ; BARBOSA, M. P.; SILVA FILHO, L. C. P. Estimation of compressive strength based on Pull-Out bond test results for on-site concrete quality control. IBRACON Structures and Materials Journal, v. 4, p. 4, 2011.

[5] SRIRAM, R. D.. Intelligent Systems for Engineering – A Knowledge-based Approach. Londres, Springer-Verlag, 1997.

[6] HAYKIN, S. Redes Neurais: Princípios e prática. Porto Alegre, Bookman, 2001. Tradução de Paulo Martins Engel.

[7] CORRÊA, L. G., Memória Associativa em Redes Neurais Realimentadas. 2004. 119p. Dissertação (Mestrado) – Instituto de Ciências Matemáticas e de Computação, Universidade de São Paulo. São Paulo, 2004.

[8] FÉDÉRATION INTERNATIONALE DE BÉTON. FIB: Bond of reinforcement concrete, State-of-art report. Bulletin Nº 10. Lausanne, Switzerland: FIB, 2000. 427p.

[9] AMERICAN CONCRETE INSTITUTE. ACI 408R: Bond and development of straight reinforcing bars in tension. Farmington Hills: ACI, 2003. 49 p.

[10] COMITÉ EURO-INTERNATIONAL DU BÉTON. RILEM/CEB/FIP RC6: Bond test for reinforcing steel - 1 - pull-out test. Paris: CEB, 1983. 3p.

[11] LORENZI, A.; SILVA FILHO, L. C. P. . Análise de Ensaios Ultra-sônicos no Concreto através de Redes Neurais Artificiais. Learning and Nonlinear Models, v. 9, p. 216-233, 2011.

[12] LORENZI, A.; SILVA FILHO, L. C. P. ;CAMPAGNOLO, J. L.. Application of Artificial Neural Network for Interpreting Ultrasonic Readings of Concrete. International Journal of Materials & Product Technology, Switzerland, v. 26, n.1/2, p. 57-70, 2006.

[13] LORENZI, A.; SILVA FILHO, L. C. P. ;CAMPAGNOLO, J. L.. Desenvolvimento de Redes Neurais Artificiais para Interpretação de Ensaios de Velocidade de Propagação de Pulso Ultrassônico no Concreto. Revista IBRACON de Estruturas e Materiais, v. 4, p. 800-830, 2011.

[14] LORENZI, A.2008LORENZI, A. ; SILVA FILHO, L.C.P. ; TISBIEREK, F. T.. Modelagem de Dados de Ensaios Ultrasônicos em Concreto através de Redes Neurais Artificiais (RNAs). Revista Abende, v. 25, p. 42-46, 2008.
[15] CAETANO, L. F. Estudo do comportamento da aderência de elementos de concreto armado em condições extremas. Dissertação (Mestrado em Engenharia Civil) - Programa de Pós-Graduação em Engenharia Civil, Universidade Federal do Rio Grande do Sul, Porto Alegre, 2008.
[16] CASTRO, C. M. Concreto de alto desempenho: estudo da aderência com a armadura sob ações repetidas. Dissertação (Mestrado em Engenharia de Estruturas) - Escola de Engenharia de São Carlos, Universidade de São Paulo, São Carlos, 2000.
[17] FERNANDES, R. M. A influência das ações repetidas na aderência aço-concreto. Dissertação (Mestrado em Engenharia de Estruturas) - Escola de Engenharia de São Carlos, Universidade de São Paulo, São Carlos, 2000.
[18] BARBOSA, M. T. G. Avaliação do comportamento da aderência em concretos com diferentes classes de resistência. Tese (Doutorado em Engenharia Civil) – Instituto Alberto Luiz Coimbra de Pós-graduação e Pesquisa de Engenharia, Universidade Federal do Rio de Janeiro. Rio de Janeiro, 2002.
[19] FRANÇA, V. H.Aderência Aço-Concreto – Uma análise do comportamento do concreto fabricado com resíduos de borracha. Dissertação (Mestrado em Engenharia) - Faculdade de Engenharia de Ilha Solteira, Universidade Estadual Paulista, UNESP, 2004.
[20] ALMEIDA FILHO, F. M. Contribuição ao estudo da aderência entre barras de aço e concreto auto-adensável. Tese (Doutorado em Engenharia de Estruturas) - Escola de Engenharia de São Carlos, Universidade de São Paulo, São Carlos, 2006.
[21] GRAEFF, A. G., Avaliação experimental e modelagem dos efeitos estruturais da propagação da corrosão em elementos de concreto armado. 2007. 184 f. Dissertação (Mestrado em Engenharia) - Programa de Pós-Graduação em Engenharia Civil, Universidade Federal do Rio Grande do Sul (UFRGS), Porto Alegre, 2007.
[22] SIMPLÍCIO, M. A. S., Estudo sobre a aderência entre barras de aço e concreto reforçado com fibras. 2008. 261 f. Tese (Doutorado) Programa de Pós-Graduação em Engenharia Civil - Universidade Federal de Pernambuco (UFPE). Recife, 2008.
[23] REIS, C. N. S., Influência da utilização de agregado miúdo de RCD na aderência aço-concreto reciclado. 2009. 171 f. Dissertação (Mestrado em Engenharia) - Pós-Graduação em Engenharia Civil e Ambiental - PPGECEA - Universidade Estadual de Feira de Santana - UEFS. Bahia, 2009.
[24] SILVA,B.V.;BARBOSA, M.P.; SILVA FILHO, L. C. P.; LORRAIN, M.S.. Experimental investigation on the use of steel-concrete bond tests for estimating axial compressive strength of concrete: part 1. IBRACON Structures and Materials Journal, v. 6 (5), p. 715-736, 2013.
[25] LORRAIN, M. S. ; CAETANO, L. F. ; SILVA, B.V. ; GOMES, L. E. S. ; BARBOSA, M.P. ; SILVA FILHO, L. C. P. Bond strength and rib geometry: a comparative study of the influence of deformation patterns on anchorage bond strength. In: PCI Annual Convention & 3rd International FIB Congress FIB, Washington D. C., 2010.
[26] FERREIRA, E. G.; GONÇALVES, R. S.; CARVALHO, E.; CUNHA, J. C.; BARBOSA, M. P.; LORRAIN M. S. Controle da Qualidade do Concreto Pelo Ensaio de Aderência “Pull out Test”. In: 53º Congresso Brasileiro do Concreto, 2011, Florianópolis/SC. Anais do 53ºCBC. São Paulo/SP: IBRACON, 2011.
[27] TOJAL, T. L., Contribuição ao estudo da aderência de barras de aço em concreto autoadensável reforçado com fibras metálicas. 2011. 116 f. Dissertação (Mestrado em Engenharia Civil : Estruturas) – Universidade Federal de Alagoas. Centro de Tecnologia. Maceió, 2011.
[28] SILVA FILHO, L. C .P.; SILVA, B.V. ; DAL BOSCO, V. I. ; GOMES, L. E. S.; BARBOSA, M.P. ; LORRAIN, M. S. Analysis of the influence of rebar geometry variations on bonding strength in the pull-out test. In: Bond in Concrete 2012 - Bond, Anchorage, Detailing. Fourth International Symposium BIC/ FIB/ Heriot-Watt University, Brescia, Italy, 2012.
[29] FRANÇA, M. B. B.; CARVALHO, E. P.; CUNHA, J. C.; RODRIGUES, C. S.; MAIA, N. S. Estudo experimental da aderência aço-concreto para barras finas de aço CA-50. In: 54º Congresso Brasileiro do Concreto, 2012, Maceió/AL. Anais do 54º CBC. São Paulo/SP: IBRACON, 2012.
[30] BAIOCHI, A. G., PIMENTEL, L. L., JACINTO, A. E.P.G.A., BARBOSA, M. P., FONTANINI, P; S.P., LORRAIN, M. Análise da aderência entre o concreto desenvolvido com resíduo de construção civil e o aço pelo método APULOT. In: 55º Congresso Brasileiro do Concreto, 2013, Gramado/RS. Anais do 55º CBC. São Paulo/SP: IBRACON, 2013.
[31] JACINTHO, A.E.P.G.A.; PIMENTA, M.T.M.; PIMENTEL, L. L.; FONTANINI, P.S.P.; BARBOSA, M. P. Estudo da aderência aço e concreto com RCD cinza em substituição aos agregados graúdos usuais. In: 55º Congresso Brasileiro do Concreto, 2013, Gramado/RS. Anais do 55º CBC. São Paulo/SP: IBRACON, 2013.
[32] GODOY, J. L.; JACINTHO, A. E. P. G. A.; PIMENTEL, L. L.; LORRAIN, M.; BARBOSA, M. P. Substituição de uma parcela do agregado natural por borracha de pneus: influência na aderência aço e concreto. In: 54º Congresso Brasileiro do Concreto, 2012, Maceió/AL. Anais do 54º CBC. São Paulo/SP: IBRACON, 2012.
[33] JACINTHO, A. E. P. G. A.; PIMENTEL L. L.; BARBOSA M. P.; FONTANINI P. S. P. Steel and concrete bond stress: a contribution to the study of APULOT tests using concrete with rubber addition. Revista IBRACON de Estruturas e Materiais, v. 7, p. 817-844, 2014.
[34] LOVERA, H.; FRUTOS, A. 2013. 136 f. Evaluación de la Tensión de Adherencia entre el Hormigón y el Acero ante la Variación de la Resistencia a Compresión mediante el Ensayo APULOT. Tesis de Ingeniería Civil, Universidad Nacional de Asunción. Asunción, Paraguay, 2013.
[35] GAVILAN, S.; SILVA, B. V.; SILVA FILHO, L. C. P.; BARBOSA, M.P. Ensayo de arrancamiento, relación recubrimiento-diámetro de barras para evitar el efecto splitting. In: XXXVI

Jornadas Sul Americanas de Engenharia Estrutural, 2014, Montevideo/Uruguay. Memórias XXXVI Jornadas Sul Americanas de Engenharia Estrutural. Porto Alegre/RS: ASAEE - Associação Sul Americana de Engenharia Estrutural, 2014.
[36] SILVA, B. V.; BARBOSA, M. P.; SILVA FILHO L. C. P.; LORRAIN M. S. Experimental investigation on the use of steel-concrete bond tests for estimating axial compressive strength of concrete. Part 2: APULOT. IBRACON Structures and Materials Journal, v. 7 (5), p. 856-878, 2014.
[37] MARTINS, J. V. R.; JACINTHO, A.E.P.G.A.; PIMENTEL, L. L.; BARBOSA, M. P.; FONTANINI, P. S. P.; LORRAIN, M. Estudo da aderência entre concreto e aço pelo ensaio APULOT utilizando concreto de alta resistência. In: 56º Congresso Brasileiro do Concreto, 2014, Natal/RN. Anais do 56º CBC. São Paulo/SP: IBRACON, 2014.