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Application of Artificial Neural Network technique in Civil Engineering

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Abstract— **This paper aimed to show possible applicability of artificial neural networks (ANN) to predict the performance of the bond between reinforcement and concrete. An ANN model is constructed, trained and tested using the available test data of 117 different pull-out cylindrical concrete specimens with an embedded reinforcing bar. The data used in ANN model are arranged in a format of four input parameters that cover the concrete compressive strength, cover thickness, embedment length, and related rib area. The ANN model, which performs in Matlab software, predicts the bond strength of anchoring capacity of the reinforcement in the concrete. The results showed that ANNs have strong potential as a feasible tool for predicting bond strength. Comparisons with empirical formula and experimental results of several different researchers show an acceptable accuracy of the proposed ANN model.**

***Keywords*— Artificial Neural Network, Bond strength, Pull-out test, compressive strength, cover**

I. Introduction

Artificial neural networks are a family of massively parallel architectures that solve difficult problems via the cooperation of highly interconnected but simple computing elements or artificial neurons. Basically, the processing elements of a neural network are similar to the neurons of the brain, which consist of many simple computational elements arranged in layers [1]. Interest in neural networks has expanded rapidly in recent years. Much of the success of neural networks is due to such characteristics as nonlinear processing and parallel processing. Recent researches are performed for the usability of ANN in the civil engineering field and especially for the concrete technology [2]. [3] utilized ANN's for the determination of concrete compressive strength. [3] suggested that ANN has a good predictive capacity. [4] utilized ANN for the determination used of compressive strength of fly ash added concretes. [4] concluded that ANN method has high predictive performance. [5] used ANN and multiple linear regression techniques for the estimation of compressive strength of steel fiber reinforced concrete. [6] concluded that ANN can be used to model the experimental relationship between the ultimate pull-out load and bond strength. [7] used ANN and regression models for the prediction of strength parameters of FRP-confined concrete.

In this work, bond strength was investigated by conducting pull-out tests on ribbed bars with a nominal diameter of 12mm. Various concrete covers were tested. Three bar types with different deformation pattern were investigated (French bar, Tunisian bar and Brazilian bar) and four concretes were studied. The effect of anchorage length has been also evaluated. Based on this experimental data, an Artificial Neural Network (ANN), was used in order to predict the ultimate pull-out load of the pull-out test specimen.

II. ARTIFICIAL NEURAL NETWORK

An easy way to comply with the conference paper formatting requirements is to use this document as a template and simply type your text into it. Artificial neural networks are a practice simulating the biological functioning of the human brain in order to imitate its reasoning capacities [8] [9]. ANN can learn via trial and error and so, to generalize. In recent years, ANNs have shown exceptional performance as a regression tool, especially when used for pattern recognition and function estimation [10] [11]. They are highly nonlinear and can capture complex interactions among input/output parameters in the system without any prior knowledge about the nature of these interactions. The principles of ANNs have been comprehensively discussed in detail elsewhere such as the history and theory of neural networks, and some indications of their future utility have been described in a plethora of published literature [12]. A very brief overview of how neural networks operate is presented in the following section.

The network consists of neurons in layers, each neuron being linked to a number of neurons in the subsequent layer. The training consists in adjusting the way a signal is processed in each connection, when the signal passes through the network. A large network with many connections demands a high number of data sets for training, whereas a smaller network can be trained satisfactorily with proportionally fewer data sets. A typical ANN model is a combination of layers made of neurons. Most widely used ANN type is multi layer perception. Multi layer perception (MLP) is composed of an input layer that takes the data in, an output layer that conveys the output of the network out and usually one but occasionally more than one hidden layer in between. In the input layer, input of the neurons are taken in from outside.

Figure 1 shows a MPL in which Nevertheless, network input of a neuron in the hidden layers or the output layer is the sum of multiplications of all the input received *(x_j)* by corresponding weights *(w_{ji})*;while output of a neuron is gotten after the network input is processed by the activation function [13] (Baillie & Mathew, 1994).

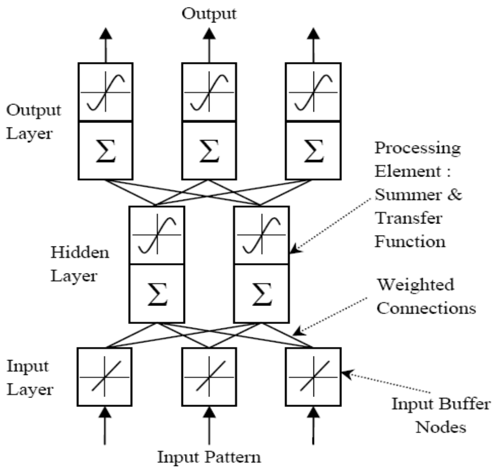

Fig.1Architecture of a Multi-Layer Perception (Baillie & Mathew, 1994)

The relationship between the inputs and the output is given by the Equation 1.

$$Y_j = F(I) = F\left(b + \sum_{i=1}^{n} w_{ji} x_j\right) \tag{1}$$

where *(n)* is the total number of input neurons, *(F)* is the activation function, *(x_j)* is ith input variable, *(w_{ji})*'s are weights for input between neuron *i* and *j* and b is weight of arc leading from the bias term. Each neuron is associated with a threshold value and an activation function. The activation function is used to compare the weighted sum of inputs and the threshold value of that neuron. If the threshold value is exceeded by the weighted sum the neuron goes to a higher state. Many different activation functions are used in different applications. Therefore, a sigmoidal activation function has been used here as follows:

$$Y_j = F(I) = \frac{1}{1 + e^{-\alpha(I-\theta_j)}} \tag{2}$$

where Y_j is the output of neuron *j*, *I* is the summation of all the weighted sums of the inputs for neuron *j*, θj is the threshold value of neuron *j*, and α is a parameter which controls the slope of the activation function.

In the present work a backpropagation learning algorithm has been used to provide satisfactory results. This algorithm necessitates the use of a continuous, differentiable weighting function. The back propagation learning is an iterated search process which adjusts the weights from output layer back to input layer in each run until no further improvement in Mean Square Error (MSE) value is found. The backpropagation algorithm calculates the error, and then used to adjust the weights first in the output layer, and then distributes it backward from the output to hidden and input neurons (Fig. 2). This is done using the steepest gradient descent principle where the change in weight is directed towards negative of the error gradient.

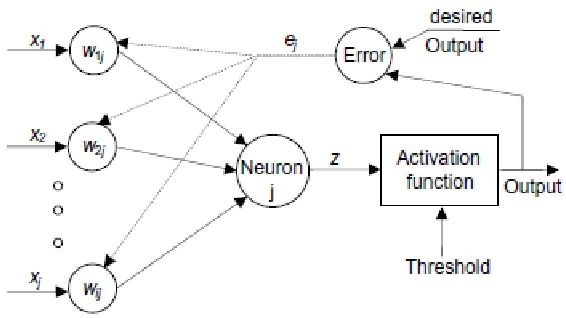

Fig. 2 Neuron weight adjustment (M.M. Alshihri et al. 2009)

The new weight is calculated as follows:

$$\Delta w_i = \alpha \Delta w_{i-1} - \eta \frac{\partial E_i}{\partial w} \tag{3}$$

where *w* is the weight between any two neurons; ∂w_i and ∂w_{i-1} are the changes in this weight at *i* and *i-1* iteration; α the momentum factor; and η is the learning rate.
E_i represents the Root Mean Square Error (RMSE) for iteration *i* as follow:

$$E_i = \sqrt{\frac{1}{N} \sum_{n=1}^{N} (e_n)^2} \tag{4}$$

where e_n is the error between actual and predicted values, and N the total number of data points in validation.

III. Experimental Programm

This investigation was designed to test the anchoring capacity of the reinforcement in the concrete. The cover thickness, concrete strength, embedment length and rib geometry or related rib area of pull-out test were considered as the main study parameters. 12 mm nominal diameter bars were selected to match typical main longitudinal steel. The study parameters were evaluated under monotonic loading in tension.

A. *Test specimens*

This investigation uses specimens in which a single reinforcing bar is embedded with a short anchorage length in a cylindrical plain concrete block [14]. This short anchorage length provides a well-defined bond zone length and supports the assumption of uniform stress and deformation fields in the zone.

The pull-out specimens were cast in especially constructed forms with the reinforcing bar. The dimensions of tested specimen were 120 mm in length, and 5.52ϕ to 13.3ϕ in diameter. The bond length is located at the top of the specimen and the rest of the specimen is de-bonded by the use of a small PVC pipe in the bottom of each specimen.

Figure 3 shows schematically a typical test specimen used in this investigation.

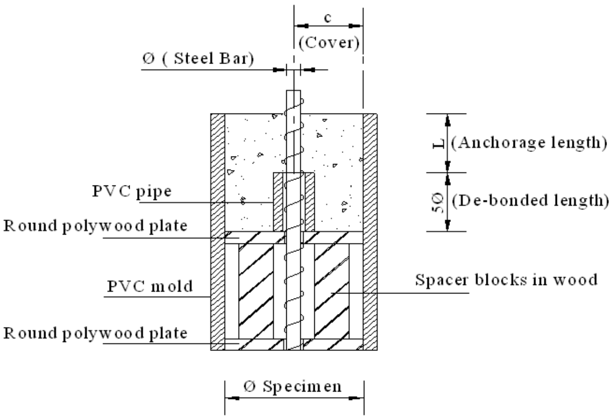

Fig.3Specimen geometry

B. *Concrete mixtures*

The plain concrete mixture used without admixtures to cast the test specimens contained a normal Portland cement of type CEM I 42.5, the cement content ranged between 250 – 400 kg/m^3 and a water cement ratio ranged between 0.45 – 0.90. The target compressive strengths (f_{c28}) for the concrete specimens ranged between 20 to 40 MPa. Local aggregates were used for the concrete mix design: 20 mm nominal maximum size crushed limestone and washed sand supplied by a local sand washing plant. The specimens were removed from their moulds 24 hours after casting and stored and cured for 28 days at the concrete laboratory, and then were transferred for the structural laboratory for testing.

C. *Reinforcement properties*

Three types of steel bar, from three different continents, have been analyzed in this study: a bar from Tunisia of nominal diameter 12mm, a bar from France of nominal diameter 12mm and a bar from Brazil of nominal diameter 12,5mm.

The surface roughness of each bar was characterized by the relative rib area (f_R).The calculation of the relative rib area is detailed in [15].

D. *Pull-out test [14]*

The pullout specimens were tested in such a way that the concrete in the development region was not in compression. The reinforcing bar was pulled from one end of the test specimen while the other unloaded end was used to measure the bar slip.

A test frame was used to carry out the experimental program. Some additional accessory parts were designed and fitted to facilitate the examination of bond strength investigation. A hydraulically controlled testing actuator with capacity of 300 kN was used to apply monotonic tensile load. The displacement was measured at the end of the unloaded steel bar by the use of the built in Linear Variable Differential Transducer (LVDT) with a 0 to 10 mm range secured in a tripod on the unloaded end of the specimen surface recorded bar slips that were archived electronically with the load readings. The typical loading rate was selected at 1.1kN/s. All tests were run under load control until failure.

A total of 117 cylindrical pull-out specimens were tested within the current investigation, a minimum of three replicate specimens were cast within a group. Only one parameter was changed at a time, while all other parameters were kept constant. For each test the mode of failure is identified.

The bond strength was calculated assuming a uniform distribution of bond stresses along the bond length. It was calculated from the ultimate pull-out load as follows:

$$\tau_u = \frac{F_u}{\pi.\phi.L} \tag{6}$$

where τ_u is the ultimate average bond strength (MPa), ϕ is the reinforcement diameter (mm), L is the bond length (mm) and F_u is the ultimate pull-out load (N).

The experimental values of the ultimate pull-out load are recapitulated in [16].

IV. ANN PULL-OUT MODEL

In this present work, a BPANN with an MPL is proposed. ANN architecture used for this study is given in Figure 4. The computer program was performed under Matlab software using the neural toolbox. In the training, in order to avoid over fitting of the network, the number of neuron of the unique hidden layer is equal to five, the sum of input neuron and the output neuron [17] [18].

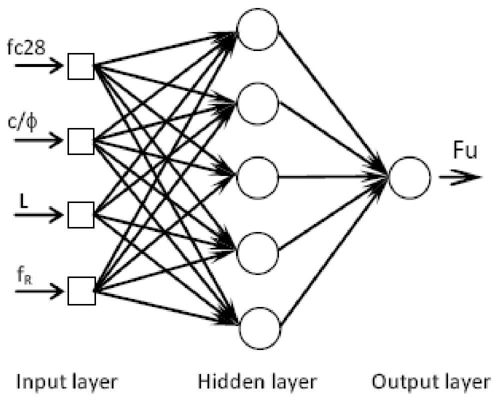

Fig.4 ANN architecture.

The database is divided into three subsets: training, testing and validation. To ensure statistical consistency of the subsets needed for the ANN model development, a random data division is used. 70% of the total database was used for the training process, 15% for the testing and 15% for the validation.

The selections of the optimum network were deduced by the minimization of the network error (Equation 4).

Predicted and measured values are presented in figure 5.

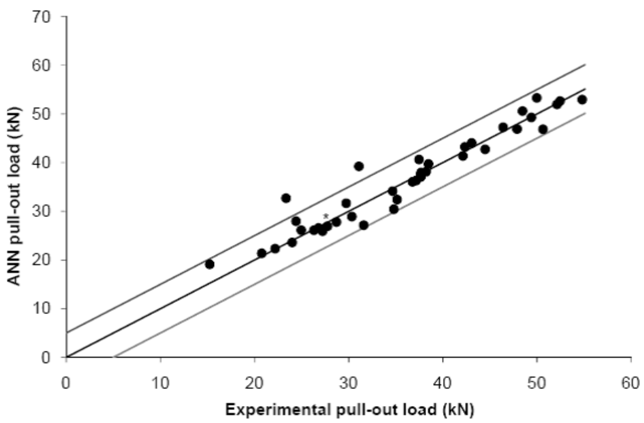

Fig. 5 ANN-predicted Vs measured ultimate pull-out load dataset.

Figure 5 shows that predicted and measured ultimate pullout loads are well correlated. The correlation coefficient R^2 is equal to 0.96. Moreover, 95% of the three subsets were located near the perfect prediction line with an absolute accuracy range of ±5kN.

V. VALIDATION OF THE ANN PULL-OUT MODEL ON EXPERIMENTAL RESULTS FROM LITTERATURE

In the literature there are several analytical and numerical models which try to represent the bond stress response in the steel-concrete interface. In those models, most of them based in experimental results, several parameters were studied such as concrete compressive strength, concrete cover, steel bar diameter, embedment length, and others. Several researchers have attempted to formulate equations that represent the bond between the reinforcing bars and concrete by means of linear or non-linear regressions from experimental results. Below is a brief description of a few:

[19] [20] proposed the following formula:

$$\tau_u = 0.083045\left[1.2 + 3\left(\frac{c}{\phi}\right) + 50\left(\frac{\phi}{L}\right)\right]\sqrt{f_c} \qquad (7)$$

where c is minimum concrete cover, in mm and f_c is the concrete compressive strength, in MPa.

[21] Chapman and Shah (1987), proposed another expression to predict bond strength as follows:

$$\tau_u = \left[3.5 + 3.4\left(\frac{c}{\phi}\right) + 57\left(\frac{\phi}{L}\right)\right]\sqrt{f_c} \qquad (8)$$

where f_c is the concrete compressive strength, in Psi.

[22] Kemp (1986), describe the equation allow calculating the average bond strength from experimental hypothesis and recommended the following formula:

$$\tau_u = 232.2 + 2.716\left(\frac{c}{\phi}\right)\sqrt{f_c} \qquad (9)$$

where f_c is the concrete compressive strength, in Psi.

[23] Al-Jahdali et al (1994), proposed a modified expression (in SI) for bond strength as follows:

$$\tau_u = \left[-0.879 + 0.324\left(\frac{c}{\phi}\right) + 5.79\left(\frac{\phi}{L}\right)\right]\sqrt{f_c} \qquad (10)$$

Figures 6 and 7 show the variation of the bond strength versus the concrete compressive strength (f_c) and c/ϕ ratio of the above equations added with the ANN model results.

The ANN model results presented bond strength values higher than almost all equations predicted values bringing a safety response. The equation from Chapman et al. had a good approach for the results of the ANN model.

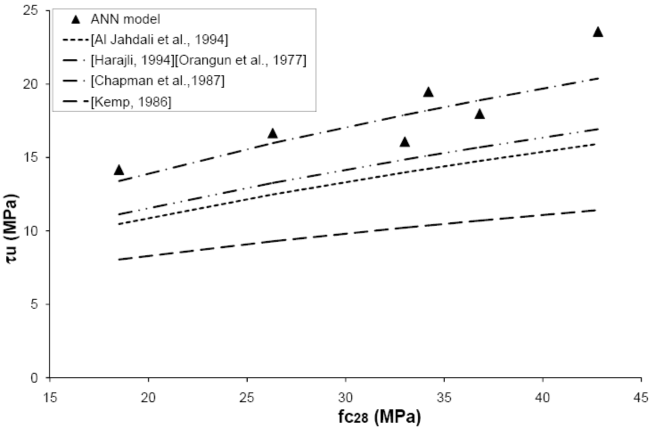

Fig. 6 Bond strength vs compressive strength

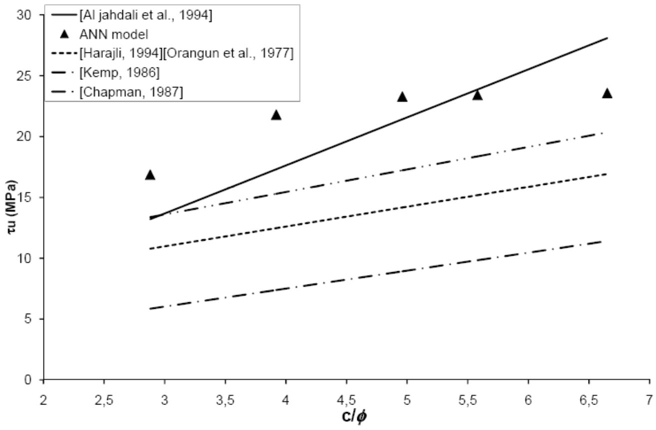

Fig. 7 Bond strength vs c/ϕ ratio

In order to check the validity of the proposed ANN model, experimental results obtained by other researchers were considered. Unfortunately, few results exactly fitting the variation range of our experimental input factors of the ANN model were available.

Table I shows concrete strength and specimen geometry parameters used by several different researchers and the ultimate bond stress measured experimentally. These parameters are used as input data for ANN model validation. In some cases, relative rib area value (f_R) is not mentioned by the authors. We take as input a mean value of the experimental range (0.074).

The experimental and the predicted ultimate bond stress are then compared in Table 4.The ANN model reproduced the experimental ultimate bond stress with a maximal COV of 20%.

VI. CONCLUSION

This paper presents a non-traditional approach to the prediction of the ultimate pull-out load based on ANN technique.

The pull-out tests were used to investigate some of the effect of the concrete strength, the cover thickness, the embedment length and the relative rib area.

TABLE I. VALIDATION OF THE ANN MODEL FOR ULTIMATE BOND STRESS PREDICTION

Ref.	f_c (MPa)	c/ϕ	L (mm)	f_R	Exp. τ_u (MPa)	ANN τ_u (MPa)	COV
[24]	34.4	6	60	0.07	12.7	15.9	20.1
[25]	45	5	80	0,079	15.1	15.2	0.6
[26]	30	5	80	0.074	10.8	10.2	5.6

The experimental results provided a database for implementing a Neural Network model for the ultimate pull-out prediction. ANN model was developed with four inputs compressive strength, c/ϕ ratio, embedment length and relative rib area values were analyzed by means of multi-layer feed forward back propagation neural network model. In the analysis, gradient descent algorithm and one hidden layer was employed.

The following conclusions may be drawn from this study:

- The results show that artificial neural networks can be implemented to predict the ultimate pull-out load from compressive strength, c/ϕ ration, embedment length and relative rib area.
- The model, trained, tested and validated according to the large database, show good accuracy in the ultimate pull-out load prediction
- Experimental results and ANN model exhibited good correlation with R^2= 0.96, the proposed ANN is a valid alternative approach to prediction and programming using artificial neural networks.
- Comparisons with empirical formula and experimental results of several different researchers show an acceptable accuracy of the proposed ANN model

REFERENCES

[1] Yeh I. . Modeling of strength of high-performance concrete using artificial neural networks. Cem Concr Res (28): pp.1797–808, 1998

[2] Subasi S, Beycioglu A . Determining the compressive strength of crushed limestone aggregate concrete using different prediction methods. e-J. N. World Sci. Acad. 3(4): pp. 580-589, 2008

[3] Lee SC . Prediction of concrete strength using artificial neural networks. Eng. Structures (25): pp. 849-857, 2003

[4] Topcu IB, Saridemir M . Prediction of compressive strength of concrete containing fly ash using artificial neural network and fuzzy logic. Computat. Mat. Sci. 41(3): pp.305-311, 2008

[5] Altun F, Kisi O, Aydin K . Predicting the compressive strength of steel fiber added lightweight concrete using neural network. Computat. Mat. Sci. 42(2): pp. 259-265, 2008

[6] Z. Dahou, Z. M. Sbartaï, A. Castel, F. Ghomari . Artificial neural network model for steel_concrete bond prediction. Engineering Structures (31): pp.1724-1733, 2009

[7] H.M. Elsanadedy, Y.A. Al-Salloum, H Abbas, S.H. Alsayed . Prediction of strength parameters of FRP-confined concrete. Composites: Part B (43): pp. 228-239, 2012
[8] Dreyfus G, et al., Réseaux de neurones-Méthodologie et applications. Eyrolles, 2002
[9]Jodouin JF. Les réseaux de neurones- principe et définitions. Paris: Hermes, 1994
[10] Mukherjee A, Biswas SN. Artificial neural networks in prediction of mechanical behavior of concrete at high temperature. Nucl Eng Des (178):pp.1–11, 1997
[11] Erdem H. Prediction of the moment capacity of reinforced concrete slabs in fire using artificial neural networks. Adv Eng Softw (41): pp.270–9, 2010
[12] Flood I, Kartam N. Neural networks in civil engineering, principle and understanding. ASCE J Comput Civil Eng 8(2):pp.131-48, 1994
[13] Baillie D, Mathew J. Diagnosis rolling element bearing faults with artificial neural network. Acoustics Australia; 22: pp.79–84, 1994
[14] Rilem "Essai portant sur l'adhérence des armatures du béton : essai par traction " , *Materials and structures*, vol. 3, n° 15, 1970
[15] Makni M. et Daoud A. (2012), "Caractérisation géométrique des barres d'acier pour béton armé par des méthodes expérimentales », Annales de bâtiments et de travaux publics, n°3/4, p47-52, 2012
[16] Makni M., Daoud A., Karray M.A. and M. Lorrain "Towards a standards pull-out test: geometrical specifications", Congrès de la FIB, Washington, USA, Mai, 2010
[17] Hecht-Nielsen, R. Neurocomputing, Addison-Wesley, Reading (MA), 1991
[18] Braham, R. and J. O. Hamblen. The design of a neural network with a biologically motivated architecture. IEEE Transactions on Neural Networks, 1990, Vol. 1, No. 3, pp. 251-262, 1990
[19] Harajli, M.H. Development/splice strength of reinforcing bars embedded in plain and fiber reinforced concrete, ACI Structural Journal 91(5): pp. 511-520, 1994
[20] C. O. Orangun, I. O. Jirsa, and J. E. Breen, A Reevaluation of Test Data on Development Length and Splices, ACI Journal, vol. 74, no. 3, pp. 114-122, 1977
[21] Chapman, R.A. and Shah, S.P. Early-age bond strength in reinforced concrete, ACI Materials Journal 84(6): pp. 501-510, 1987
[22] Kemp, E.L.,. Bond in reinforced concrete: behavior and design criteria, ACI Journal, 83(1):pp.50-57, 1986
[23] Al-Jahdali, F.A., Wafa, F.F. and Shihata, S.A. Development length for straight deformed bars in high-strength concrete; ACI Special Publication (SP-149), pp.507-522. 1994
[24] Castel A, Vidal T, Viriyametanont K, Raoul F. ; Effect of reinforcing bar orientation and location on bond with selfconsolidating concrete. ACI Struct; 103 (4):pp. 559_67, 2006
[25] Daoud A, Lorrain M, Elgonnouni M. . Résistance à l'arrachement d'armatures ancrées dans du béton autoplaçant. Mater Struct; 35(7): pp. 395_401, 2002
[26] Menezes de Almeida Filho F et al.; Bond-slip behavior of self-compacting concrete and vibrated concrete using pull-out and beam tests. Mater Struct 41: pp.1073–1089, 2008