Prediction of shear strength of reinforced concrete beams using Artificial Neural Network and evaluated by Finite Element Software

Dr. Luay Mohammed Al-Shather* [1], Statistic Ms. Azhar Mohammed Redah [2]

ABSTRACT-In this paper, the Artificial Neural Network (ANN) and the Adaptive Neuro-Fuzzy Inference Framework (ANFIS) are utilized to foresee the shear quality of Reinforced Concrete (RC) shafts, and the models are contrasted and American Concrete Institute (ACI) and Iranian Concrete Institute (ICI) observational codes . The ANN display, with Multi-Layer Perceptron (MLP), utilizing a Back-Propagation (BP) algorithm, is utilized to foresee the shear quality of RC pillars. Six vital parameters are chosen as info parameters counting: concrete compressive quality, longitudinal reinforcement volume, shear traverse to-profundity proportion , transverse support, compelling profundity of the bar and bar width. The ANFIS demonstrate is additionally connected to a database and results are contrasted and the ANN show and exact codes. The primary request Sugeno fuzzy is utilized in light of the fact that the resulting some portion of the Fuzzy Inference System (FIS) is direct and the parameters can be assessed by a basic minimum squares blunder technique. Correlation between the models and the observational equations demonstrates that the ANN display with the MLP/BP algorithm gives better expectation to shear quality. In addition, ANN and ANFIS models are more precise than ICI and ACI exact codes in expectation of RC bars shear quality. These study were verified by using powerful finite element program and gave suitable agreement with NNA approaches.

KEYWORDS- Reinforced concrete beam, Shear strength, ANN , Adaptive neuro-fuzzy inference system, Finite Element software (Abaqus), ACI code.

1 INTRODUCTION

These days, the utilization of concrete auxiliary individuals is expanded. The strength of individuals in the plan and conduct of shear strength is an imperative issue in auxiliary outline. There are a few methods of disappointment in concrete auxiliary individuals. Because of the delicacy of concrete structures, shear disappointment is a standout amongst the most critical and bothersome methods of disappointment. Consequently, Reinforced Concrete (RC) individuals are utilized to oppose shear disappointment. In view of the unpredictability of shear instruments of reinforced concrete shafts and different impacting parameters, it is hard to build up a general model to give exact estimation of shear strength. Consequently, correct estimations of shear strength are obscure. A few exact recipes are proposed in the writing and concrete codes for the expectation of RC bars protection.

[1] Lecturer, the University of Kufa, Faculty of Engineering, Structural and Water Resources Department, Iraq – Najaf. Email: luay.albothabhak@uokufa.edu.iq , Tel: + 07801007962
[2] Statistic , the University of Kufa, office of the President of the university. Email; azhar.almusawi@uokufa.edu.iq

The American Concrete Institute (ACI) code [1] has been generally utilized as a part of basic plan. Likewise. Each of the proposed experimental equations in concrete codes yields great outcomes only for a particular dataset. In the most recent decades, various works have been embraced to enhance the capacity of exact equation to anticipate the shear conduct of concrete auxiliary individuals.

In late decades, Artificial Neural Networks (ANN) and Versatile Neuro-Fuzzy Inference Systems (ANFIS) have been used to anticipate solid properties. ANN is a capable apparatus for framework demonstrating in an extensive variety of uses. Be that as it may , in spite of the superb order limits of the last mentioned, its advancement can be time-consuming and computer-intensive . The most essential preferred standpoint of the ANN show is that the need of the useful relationship among the different factors isn't required. The ANNs consequently assemble a relationship for arrange engineering as trial information through a learning calculation.

Kasperkiewicz et al. [2] applied ANN of the fuzzy type for predicting the strength properties of High-Performance Concrete (HPC) mixes. Yeh [3] used augment- neuron networks to model concrete strength. Guang and Zong [4] predicted the compressive strength of concrete by ANN. Waszczyszyn and Ziemianski [5] used ANN for the mechanics of structures and materials. Bai et al. [6] used ANN to predict the workability of concrete with cement replacement materials. Hadi [7] proved that ANN is more accurate and easy to implement compared to conventional methods for concert structural design. Oreta and Kawashima

[8] applied the neural network in the modeling of the confined compressive strength and strain of circular concrete columns. In addition, Lee [9] used ANN for concrete strength prediction. Kim et al. [10] applied ANN for estimation of concrete strength with concrete mix parameters. Oreta [11] simulated size effect on the shear strength of RC beams using a neural network. Mansour et al. [12] used ANN to predict the shear strength of RC beams. Cladera and Mari [13] used ANN in beams with stirrups for the shear design procedure of normal and high strength reinforced concrete beams. Abdalla et al. [14] simulated the shear of RC beams with ANN.

2. Expectation of shear strength of reinforce concrete beams.

Shear disappointment is a standout amongst the most imperative ideas in concrete basic members. Shear disappointment is caused by shear forces. RC members oppose shear force utilizing a few instruments. The shear disappointment is endured in RC shafts by giving web reinforcement. The web reinforcement for the most part takes the type of vertical stirrups or the 45° bars that surround the longitudinal bars along the characteristics of the pillar. The required shear strength to be given by the web reinforcement is generally figured by recipes in solid codes. The required region of web reinforcement or dispersing of the stirrups can be resolved in view of the measure of anticipated shear strength [11]. In this paper, diverse techniques, for example, observational codes and ANN and ANFIS models, are connected to foresee the shear strength of RC members.

2.1. EMPIRICAL ACI CODE

The ACI empirical code are different proposed formulas that are used in the design of concrete structural members. For a member subjected to shear and flexure only,

Table 1: ACI formulas for shear strength of RC beam.

Code	Formula
ACI (N)	$V_c = (\frac{\sqrt{f'_c}}{7} + \frac{120}{7}\rho_w \frac{V_u d}{M_u})\, b_w d \leq 0.3\sqrt{f'_c} b_w d,\ \frac{V_u d}{M_u} \leq 1$ $V_s = \frac{A_v f_y d}{S}(\sin\alpha_s + \cos\alpha_s) \xrightarrow{\alpha=90^\circ} V_s = \frac{A_v f_y d}{S}$

the ACI formulas are presented in Table 1 calculating the concrete shear strength in the absence of axial force and web reinforcement. For the presented formulas of Table 1, f'c and fc are concrete compressive strength in MPa and kg/cm2, respectively; ρw is the longitudinal steel ratio given by As/bwd; Vu is factored shear force; Mu is factored bending moment occurring simultaneously with Vu at the section considered; bw is beam width (cm); d is effective depth of the beam (cm); Av is shear reinforcement area (cm^2); fy is yield strength of shear reinforcement (kg/cm^2); S is stirrups spacing (cm); and αs is stirrups inclination angle.

2.2. ANN AND ANFIS MODELS

ANN and ANFIS models are also suggested to compare with empirical formulas in the prediction of RC beams shear strength. An introduction and different application of the ANN model [2–14] and the ANFIS model [15–20] are presented in the literature. For application of ANN and ANFIS models in any field, different input parameters should be considered. In this paper, six important parameters are selected as input parameters for the prediction of the shear strength of RC beams including: concrete compressive strength (fc), longitudinal reinforcement volume (ρw), shear span-to-depth ratio (S/d), transverse reinforcement (ρl), effective depth of the beam (d) and beam width (bw). Furthermore, in ANN and ANFIS models, two sets of dataset, named training and testing datasets, are used. The training dataset is used to train the network, whereas the testing dataset is selected to verify the accuracy of the trained models for the prediction of the shear strength of RC beams.

Additionally, choosing the suitable number of hidden neurons and number of hidden layers are significant parameters in obtaining a precise ANN show. Furthermore, the best choice of enactment work considerably affects the capacity of the model. The number of hidden layers and number of nodes in hidden layers are normally determined through trial and error strategies or using proposed rules. For instance, in light of the technique recommended by Anderson and McNeill [15], the number of upper bound processing nodes of the hidden layers can be ascertained by dividing the number of input– yield sets of the training set by the aggregate number of input and yield nodes of the system, increased by a scaling factor in the vicinity of five and ten .Bigger scaling factors are utilized for moderately uproarious information [16] .The ANFIS is considered here as another technique in combining the upsides of FIS and ANN. ANFIS is a class of versatile system that is practically proportionate to FIS. The to start with arrange Sugeno fluffy is utilized on the grounds that the subsequent piece of the FIS is linear and the parameters can be evaluated by a straightforward slightest squares error strategy. ANFIS is a case of models in which the shape parameters of the enrollment capacities of fluffy preface factors, and also the linear parameters of the subsequent piece of fluffy guidelines in a Takagi– Sugeno FIS ,are tuned using ANNs. ANFIS is a Sugeno kind of FIS in which the issue of calibrating enrollment elements of introduce factors is done by a feed-forward neural network and which joins the benefits of both a neural network and FIS [17].

To demonstrate the productivity of the proposed techniques, the experimental datasets by Bentz [18] and Bohigas [19] are utilized what's more, the shear strength of RC beams is ascertained utilizing all proposed techniques. Likewise, to assess the execution of the ACI and ICI codes, estimations of the shear strength of RC beams from codes are contrasted and estimated experimental data . Correlations between watched (experimental) and anticipated shear strength are appeared in Figure 1. It can be seen that the predicted shear strengths are more scattered from the watched shear strengths .For development of the ANN and ANFIS models, the 123 datasets are isolated into two separate datasets arbitrarily ,named preparing and testing datasets. 120 datasets are utilized for preparing the system and the rest of the 23 datasets are considered as testing datasets of the system. Figure 2 appears the architecture of the last ANN demonstrate. Tables 2 and 3 demonstrate the scope of various input– yield parameters utilized for preparing and testing datasets, individually. Info parameters are chosen, in view of Bentz [18] and Bohigas [19] research . Different blends of information parameters can be considered in building up the ANN models, utilizing experimental datasets , prompting the development of six sorts of architecture. At each step, one of the parameters is added to the system as the input parameter. It is demonstrated that the system with every one of the six information parameters has more exactness and ability to foresee the shear strength of RC beams.

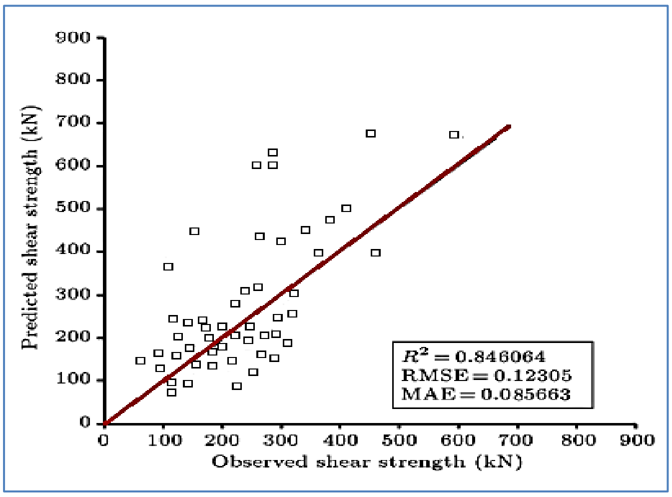


Figure 1: Rapprochement between observed and empirical ACI code

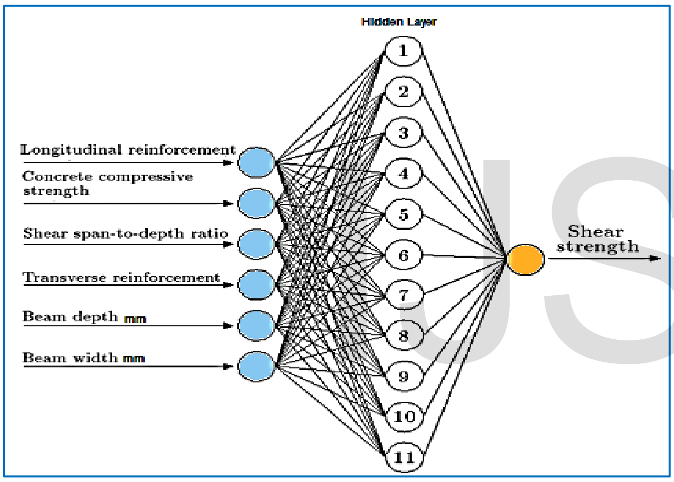


Figure 2: Architecture of ANN model.

Table 2: Range of [input–output parameters] for training data used in ANNs model.

	Parameter	Training data (120 data set)	
		Minimum	Maximum
Input parameters	b - Beam width (mm)	120	420
	d- Beam depth (mm)	200	820
	f'c - Concrete compressive strength (MPa)	25.70	65
	ρw - Longitudinal reinforcement (%)	0.5	5.8
	Av - Shear reinforcement (%)	0.33	3.57
	a/d - Shear span-to-depth	2.48	5.0
Out put	Vu - Shear strength (KN)	63	785

Table 3: Range of [input–output parameters] for testing dataset used in ANNs model.

	Parameter	Training data (25 data set)	
		Minimum	Maximum
Input parameters	b - Beam width (mm)	110	420
	d- Beam depth (mm)	200	820
	f'c - Concrete compressive strength (MPa)	28	70
	ρw - Longitudinal reinforcement (%)	0.5	5.4
	Av - Shear reinforcement (%)	0.35	3.66
	a/d - Shear span-to-depth	2.6	4.0
Out put	Vu - Shear strength (KN)	71	740

For development of ANN models, there is no hypothetical reason ever to utilize more than two hidden layers. For some functional issues, there is no motivation to utilize any more than one hidden layer. Those issues that require two hidden layers are just infrequently experienced in real-life situations [20]. The quantity of hidden layers is viewed as equivalent to one to enhance the effectiveness and similarity of the model in anticipating and testing the exactness of the new exploratory datasets speedier and all the more effectively, with a lower number of weights also, associations in the neurons. For choosing the quantity of neurons in the hidden layer, the 20 models are built utilizing 2– 22 neurons, individually, and for each model, the RMSE esteem is figured. Figure 3 demonstrates an ideal model is gotten when 11 neurons are utilized as a part of the hidden layer. Thus , an ANN display with 6 input parameters, and 1 hidden layer with 11 neurons, in view of the MLP/BP calculation, is built .To maintain a strategic distance from over-preparing of the model, the system is prepared by at first performing with bring down iterations. The quantity of iterations is expanded progressively (with an equivalent advance), while the process is halted when the execution begins to drop. In this way, the ideal ANN demonstrate is distinguished in 740 iterations.

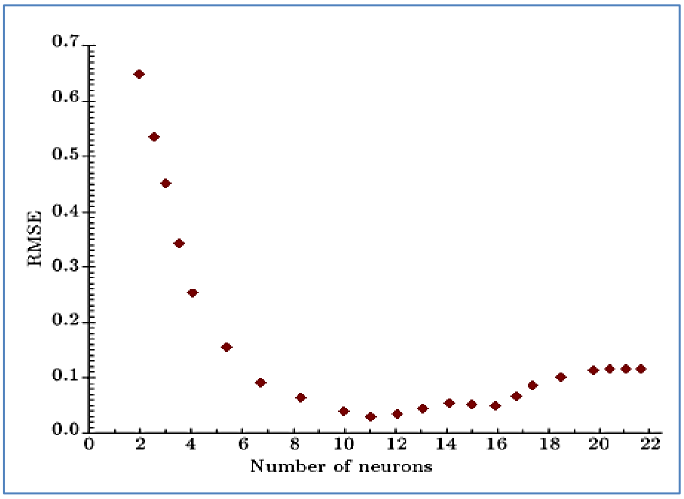


Figure 3: Selection of number neurons in hidden layer.

Examination consequences of the ANN show with exploratory comes about are appeared in Figure 4. Figure 5 demonstrates the examination between the forecast of the shear quality of the preparation and testing information, as given by ACI code and the ANN show. It is clear that the execution of the ANN MLP/BP display is much superior to anything ACI code .For the ANFIS demonstrate, the same as the ANN show, 120 data sets are utilized as preparing, and 25 informational collections as testing information. After preparing, each of the 120 informational indexes are utilized for testing the model to confirm the precision of the anticipated estimations of shear quality. ANFIS recognizes a capacity for mapping the information factors to the yield layer. These anticipated esteems are contrasted and watched information to demonstrate the execution of the ANFIS show for the forecast of RC beam shear capacity. Figure 6 demonstrates the correlation amongst watched and anticipated estimations of the ANFIS display . As can be seen from this figure, ANFIS has performed well in anticipating the shear quality. Figure 7 demonstrates the examination between the expectation of the shear quality of the preparation and testing information, as given by ACI code and the ANFIS demonstrate.

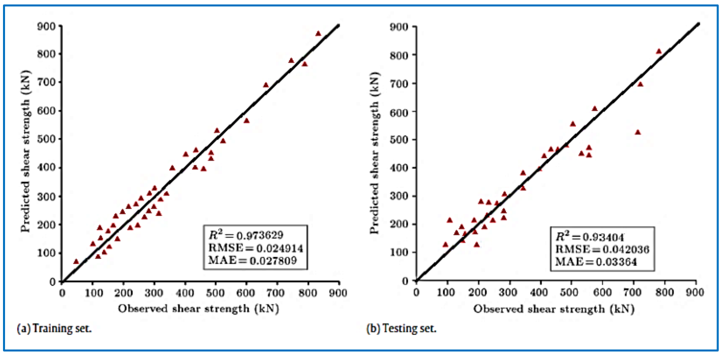


***Figure 4**: Plot of observed and predicted shear strength for ANN model.*

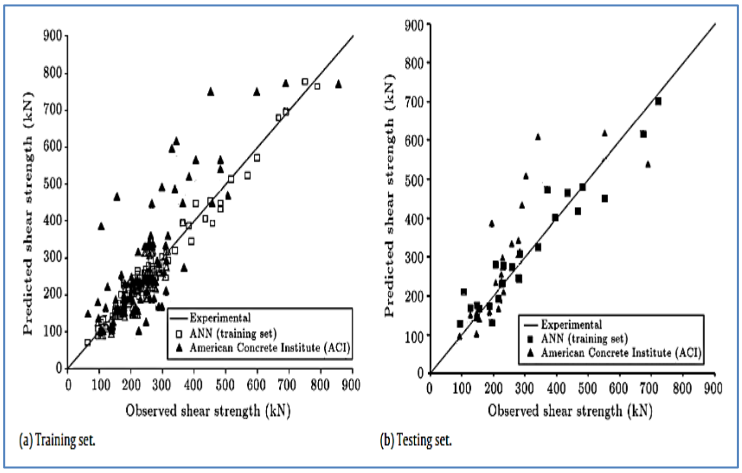


Figure 5: Comparison between ACI code and ANN model.

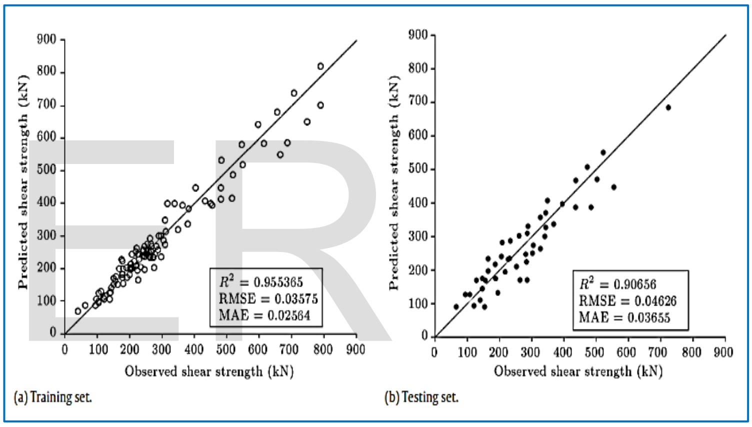
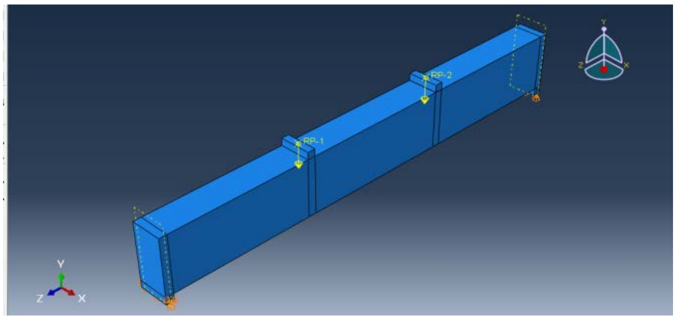


Figure 6: Plot of observed and predicted shear strength for ANFIS model.

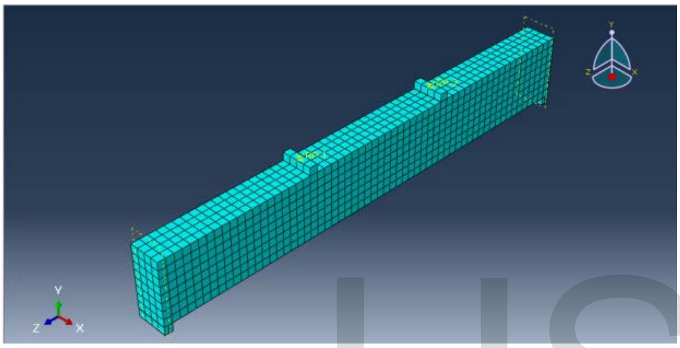
2-3 Verification by Finite Element Program

2-3-1 Description of FE-model

ABAQUS/ACE 2016 [21]was used to model the three beams was chosen from pervious data set . A 3D plane stress FE model has been made based on the geometry of tested beam in figure 7(a-b). Figure 8 shows the geometry of model, arrangement of transverse and longitudinal reinforcement and applied boundary conditions. Because of the symmetry, only half of the beam modelled. In the modelling of roller support, no special element has been used to relief the uplift forces during rebound. For this reason, the response of model is only valid up to the maximum response. As it was discussed in section 4.3, in the present analysis, no bond-slip model was considered.



(a)



(b)

Figure 7: The geometry of tested beam (a-boundary condition, b- Beam Mesh)

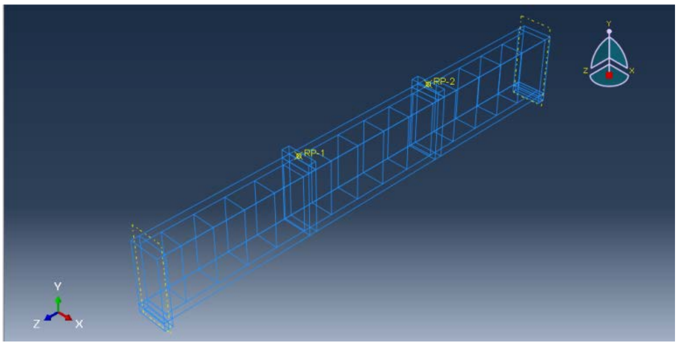


Figure 8: Geometry of model, arrangement of transverse and longitudinal reinforcement and applied boundary conditions.

2-3-2 Finite Element Results

The finite element analysis for specimens shows good convergence with excremental investigation as shown in table 3 and figure 9.

Beam No.		1	2	3
B (mm)		200	250	300
D(mm)		400	450	500
Main reinforcement %		0.5	0.7	1.0
Shear reinforcement %		0.33	0.33	0.33
Concrete compressive strength (MPa)		25.7	25.7	25.7
Vu - Shear strength (KN)	Abaqus	82.02	97.21	183.4
	ANN	79.66	92.89	181.7

Table 3: properties of tested beams by finite element software in its results.

3- Conclusions

The primary objective of the present investigation is to outline and create ANN and ANFIS models for assessing RC beam shear capacity . The exhibitions of the models were assessed and the outcomes were contrasted and observational ACI code. A few experimental recipes were utilized for processing the shear quality of RC beams in code. The models were connected in the expectation of the shear protection quality of RC beams. Results demonstrate that the ANN show with the MLP/BP calculation given a superior forecast of shear quality than the ANFIS display. Likewise, ANN and ANFIS models are more exact than experimental ACI code. Also, the expectations of ANN show were appropriated around exploratory outcomes, while ACI were more scattered from exploratory outcomes, showing that they predominately under-appraise the shear strength. This study conforming with finite element program having powerful tools to analysis the randomly selected specimens and its give suitable results for verification study.

4- References

[1] Buildings code requirements for structural concrete (ACI 318-08), American Concrete Institute (ACI), Detroit (MI) (2008).

[2] Kasperkiewicz, J., Racz, J. and Dubrawski, A. ''HPC strength prediction using artificial neural networks'', J. Comput. Civil Eng., ASCE, 9(4), pp. 279–284 (1995).

[3] Yeh, I.C. ''Modeling concrete strength with augment-neuron networks'', J. Mater. Civ. Eng., 10(4), pp. 263–268 (1998).

[4] Guang, N.H. and Zong, W.J. ''Prediction of compressive strength of concrete by neural network'', Cem. Concr. Res., 30, pp. 1245–1250 (2000).

[5] Waszczyszyn, Z. and Ziemianski, L. ''Neural networks in mechanics of structures and materials—new results and prospects of applications'', J. Comput. Struct., 79, pp. 2261–2276 (2001).

[6] Bai, J., Wild, S., Ware, J.A. and Sabir, B.B. ''Using neural networks to predict workability of concrete incorporating Meta kaolin and fly ash'', Adv. Eng. Softw., 34, pp. 663–669 (2003).

[7] Hadi, M. ''Neural networks applications in concrete structures'', J. Comput. Struct., 81, pp. 373–381 (2003).

[8] Oreta, A.W.C. and Kawashima, K. ''Neural network modeling of concrete compressive strength and strain of circular concrete columns'', J. Struct. Eng., ASCE, 29(4), pp. 554–561 (2003).

[9] Lee, S.C. ''Prediction of concrete strength using artificial neural networks'', Eng. Struct., 25, pp. 849–857 (2003).

[10] Kim, J.I., Kim, D.K., Feng, M.Q. and Yazdani, F. ''Application of neural networks for estimation of concrete strength'', J. Mater. Civ. Eng., 16(3), pp. 257–264 (2004).

[11] Oreta, A.W.C. ''Simulating size effect on shear strength of RC beams without stirrups using neural networks'', Eng. Struct., 25(5), pp. 681–691 (2004).

[12] Mansour, M.Y., Dicleli, M., Lee, J.Y. and Zhang, J. ''Predicting the shear strength of reinforced concrete beams using artificial neural networks'', Eng. Struct., 26, pp. 781–799 (2004).

[13] Cladera, A. and Mari, A.R. ''Shear design procedure for reinforced normal and high-strength concrete beams using artificial neural networks. Part II: beams with stirrups'', Eng. Struct., 26(7), pp. 927–936 (2004).

[14] Abdalla, J.A., Elsanosi, A. and Abdelwahab, A. ''Modeling and simulation of shear resistance of R/C beams using artificial neural network'', J. Franklin Inst., 344(5), pp. 741–756 (2007).

[15] Anderson, D. and McNeill, G. Artificial Neural Networks Technology, Rome Laboratory, NY, Rome, NY (1992).

[16] Rasa, E., Ketabchi, H. and Afshar, M.H. ''Predicting density and compressive strength of concrete cement paste containing silica fume using artificial neural network'', Sci. Iran., Trans. A: Civ. Eng., 16(1), pp. 33–42 (2009).

[17] Kazeminezhad, M.H., Etemad-Shahidi, A. and Mousavi, S.J. ''Application of fuzzy inference systems in prediction of wave parameters'', Ocean Eng., 32(14), pp. 1709–1725 (2005).

[18] Bentz, E.C. ''Sectional analysis of reinforced concrete members'', Ph.D. Thesis, Department of Civil Engineering, University of Toronto (2000).

[19] Bohigas, A.C. ''Shear design of reinforced high-strength concrete beams'', Ph.D. Thesis, Department of Construction Engineering, Polytechnic University of Catalonia, Barcelona (2002).

[20] Masters, Timonly, Practical Neural Network Recipes in C + +, Morgan Kaufmann (1993).

[21] Abaqus / ACE 2016