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Prediction of shear capacity of single anchors located near a concrete edge using neural networks

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Abstract

A feed forward back-propagation neural network model for predicting the shear capacity of anchor bolts located near a concrete edge is proposed. In the developed neural network, the neurons of the input layer represent the anchor outside diameter, concrete compressive strength, anchor embedment depth and the edge distance from the anchor bolt to the edge of concrete in the direction of the shear force. One neuron is used in the output layer to represent the concrete shear capacity of the anchor bolts. A database of 205 experiments available from previous laboratory anchor tests was utilised to train, validate and test the developed neural network.

Predictions of the concrete shear capacity of anchors using the trained neural network are in good agreement with experimental results and those calculated from the concrete capacity design method. A parametric study has been conducted using the trained network to study the importance of different influencing parameters on the concrete shear capacity of anchor bolts. It has been shown that the concrete edge distance in the direction of the applied load has the most significant effect on the concrete shear strength of anchors.

Keywords: Shear; Anchors; Concrete; Neural networks; Database; Capacity

1. Introduction

Anchors are commonly used to attach structural steel members to concrete and transfer loads into concrete. In many situations, anchors in concrete are required to resist shear forces such as those connecting steel beams to reinforced concrete columns and steel columns to concrete foundations. When anchors under shear are installed close to the edge of concrete members, concrete breakout failure is likely to occur and the failure load associated with it is not easily predictable.

Artificial neural networks (ANNs) are defined as computing systems made up of a number of simple, highly interconnected processing elements called 'neurons'. The networks are represented by connective weights between the neurons. These weights are the parameters that define the non-linear function performed by the neural network. The process of determining these weights is called 'training' or 'learning' and depends on the presentation of as many reliable training patterns as possible. ANNs are capable of performing an amount of generalisation from the data entries on which they are trained.

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In recent years, artificial neural networks (ANNs) have been applied to many reinforced concrete problems. ANNs have been successfully used in concrete mix-design [1–6], estimating the shear capacity of reinforced concrete deep beams [7,8], evaluating the capacity of slender reinforced concrete columns [9] and predicting deflections of reinforced concrete beams externally strengthened with FRP laminates [10]. The current paper investigates the feasibility of using artificial neural networks to evaluate the concrete breakout capacity of anchors in shear. The worldwide anchor database compiled by the ACI committees 349 and 355 is used to train, validate and test the developed artificial neural network. Comparisons between predictions obtained from the trained neural network and those from the concrete capacity design method are presented.

2. Failure modes of anchors in shear

Anchor bolts loaded in shear exhibit different modes of failure as shown in Fig. 1. In principle, they can be categorised as: steel or concrete failures. Steel failure in shear is generally characterised by bending of the anchor shaft, eventually leading to yield and rupture of the anchor shaft [11,12]. Due to the high local pressure in front of the anchor, a local concrete crushing may occur near the upper surface of the concrete before failure of anchors installed far away from the concrete edge (Fig. 1(a)). The concrete breakout failure mode [11–13] usually occurs when the anchor is located close to the free edge of concrete and cannot be avoided by increasing the anchor embedment depth [12,14] as shown in Fig. 1(b). The formation of the full concrete half-cone may be limited by spacing between anchors or edge condition (as shown in Fig. 1(c)) or by the depth of the concrete member (Fig. 1(d)).

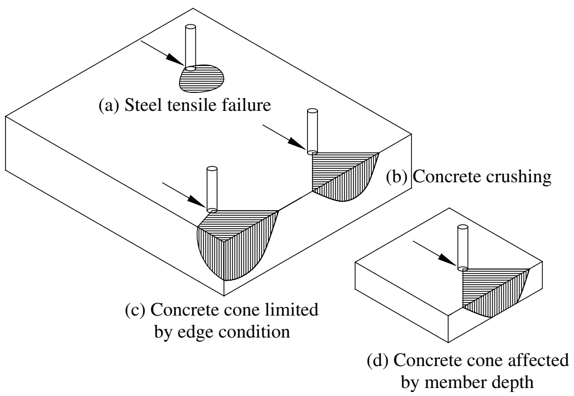


Fig. 1. Failure modes of anchors under shear loading.

3. Concrete breakout capacity of anchors in shear

The shear capacity of anchors corresponding to the concrete breakout body is influenced by the concrete tensile strength, anchor diameter, concrete edge distance and embedment depth [12,14]. However, many procedures were proposed to evaluate the concrete shear capacity of anchors [13,14], a complete analytical determination of the concrete shear capacity is not yet available [12]. The following two methods are therefore derived empirically, taking account of experimental observation and calibration.

3.1. 45° Concrete cone method

The shear capacity V_b of an individual anchor exhibiting a lateral concrete half-cone failure mode (see Fig. 2) is calculated by assuming a uniform stress of f_t ($= 0.33\sqrt{f'_c}$, where f'_c = cylinder compressive strength in N/mm^2) acting on the projected area of the failure cone, taking the inclination α between the failure and concrete surfaces as 45° [12,13]:

$$V_b = 0.48\sqrt{f'_c}c_1^2 \tag{1}$$

where c_1 = distance in mm from centre of the anchor to the edge of concrete in the direction of shear force as shown in Fig. 2. The ACI 349-85 [15], which is concerned with nuclear related structures, adopted Eq. (1) to estimate the concrete shear capacity of single anchors.

3.2. Concrete capacity design method

Based on regression analysis of a large number of tests with headed, expansion, and undercut anchors, the concrete breakout capacity of an individual anchor in a thick un-cracked concrete member under shear loading towards the free edge is [14]:

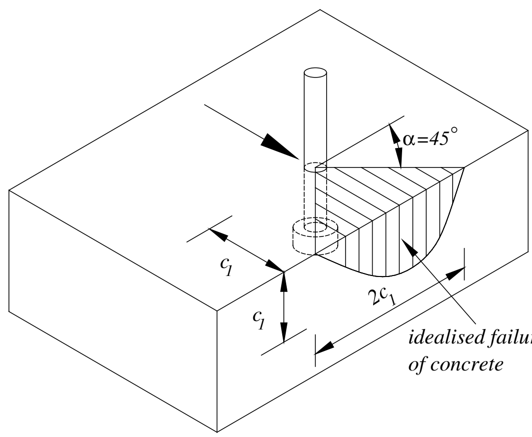


Fig. 2. Idealised concrete breakout cone of anchors in shear [15].

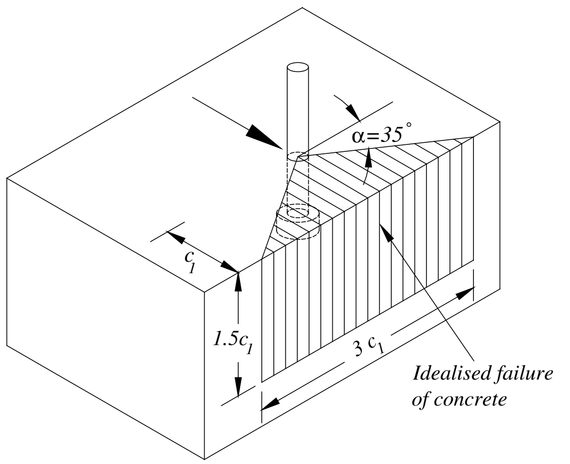


Fig. 3. Idealised concrete breakout pyramid of anchors in shear (CCD method).

$$V_b = \left(\frac{l}{d_o}\right)^{0.2}\sqrt{d_o}\sqrt{f'_c}c_1^{1.5} \tag{2}$$

where d_o = outer diameter in mm of anchor, c_1 = edge distance in mm in loading direction (see Fig. 3), f'_c = compressive strength in N/mm^2 of concrete and $l(\leqslant 8d_o)$ = activated load-bearing length in mm of anchors = h_{ef} for anchors with a constant overall stiffness or $=2d_o$ for torque-controlled expansion anchors. The concrete capacity design (CCD) method approximates the fracture body of concrete as a half-pyramid, assuming an angle α of failure of 35° as shown in Fig. 3. The concrete shear capacity calculated using Eq. (2) does not increase with the failure surface, which is proportional to c_1^2 as the case of Eq. (1), due to the size effect. The concrete shear capacity given by Eq. (2) is also affected by the anchor stiffness and diameter. The ACI 318-02 Building Code [16] provided provisions pertaining to anchoring to concrete that are mainly based on the CCD method (Eq. (2)) to calculate the concrete breakout strength of single cast-in and post-installed mechanical anchors in shear.

4. Experimental data on anchors in shear

A worldwide database for mechanical anchors was originally compiled by Fuchs and Breen (cited in Farrow et al. [17]) using results of tests on anchor bolts, headed studs, undercut anchors and expansion anchors conducted in both Europe and USA. Additional test results were obtained and added to the database by Klingner and his associates at the University of Texas, who maintains it on behalf of the ACI committees 349 and 355. This database is placed in the public domain. The database includes results of anchors tested in shear and tension for a wide range of anchor configurations in cracked and un-cracked concrete. The database contains test data for multiple anchors and for single anchors located close to a free edge. The following criteria were considered in selecting the tests employed to train, validate and test the developed neural network model:

- Single anchors tested under short term static shear loads; those tested under tensile loads are not considered.
- Tests carried out in un-cracked and un-confined thick concrete; tests of anchors conducted in cracked or confined concrete are not included.
- Only tests where a concrete breakout failure occurred are taken into consideration. Anchors tests affected by edge distance in a direction perpendicular to the shear loading direction or concrete member thickness are excluded. Also, anchors failed due to anchor shaft yield or rupture are ignored.

Considering only those tests that satisfy the above-mentioned criteria resulted in a reduced database of 205 data entries. The range of different input parameters in the reduced database is given in Table 1.

Table 1
Range of input parameters of the database used to train the ANN

Neural network input parameters	Range	
	Minimum	Maximum
Cylinder compressive strength of concrete, f'_c (MPa)	21.72	73
Embedment depth, h_{ef} (mm)	60	306
Outer diameter of anchor, d_o (mm)	12	32
Concrete edge distance, c_1 (mm)	50	203
Shear capacity of anchors (kN)	5.7	163.38

5. Overview of back-propagation neural networks

The most widely used neural network in civil engineering applications is the back-propagation networks [18–20]. Back-propagation neural networks can establish mappings between inputs and outputs based on historical data, without any explicit model being defined, even if those mappings are highly non-linear. The back-propagation algorithm is a systematic way to update the neuron weights of multi-layer feed forward networks composed of an input layer, which represents the input data, an output layer, which computes the neural networks output, and one or more intermediary layers, called hidden layers as shown in Fig. 4. The network architecture or topology is obtained by identifying the

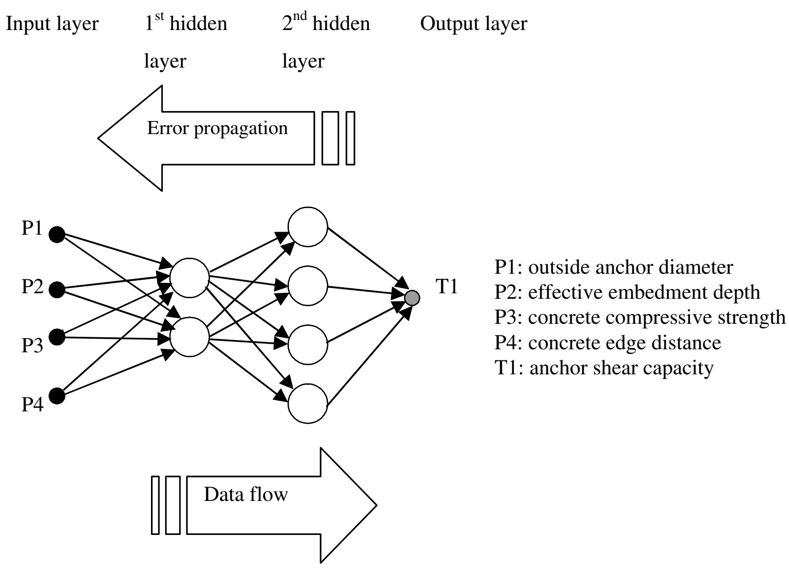


Fig. 4. Architecture of the developed neural network.

number of hidden layers and the number of neurons in each hidden layer. There is no specific rule to determine the number of hidden layers or the number of neurons in each hidden layer. The network learns by comparing its output for each pattern with a target output for that pattern, then calculating the error and propagating an error function backward through the neural network. The capacity of the network to learn the patterns on the training set is called convergence and the capacity to respond correctly to new patterns is known as generalisation. The process of defining the network architecture is a compromise between generalisation and convergence [2,6,21]. To use the trained neural network, new values for the input parameters are presented to the network. The network then calculates the neuron outputs using the existing weight values developed in the training process.

6. Construction of ANN model

6.1. MATLAB neural network toolbox

The neural network toolbox available in MATLAB version 6 [21] was utilised to construct the proposed neural network in this study. Neural network toolbox can be rapidly implemented and large scale problems can be tested conveniently [22]. The NN toolbox enables modelling the problem using back-propagation neural networks, radial basis neural networks and recurrent neural networks with a wide range of transfer functions, learning techniques, network topology, performance optimisation and performance functions.

6.2. Preparation of the training data

The multi-layer feed forward back-propagation technique is implemented to develop and train the neural network of the current research and both the sigmoid and linear transfer functions [21] are adopted. Rafiq et al. [23] explained that one of the essential measures to improve the training process is data scaling. In case of the sigmoid transfer function, the output is in the range $(0,1)$, and the input is sensitive in a range not much larger than $(-1,+1)$. Therefore, when the inputs are scaled to be between $(-1,+1)$, the learning speed will be significantly improved. Scaling of data can be linear or non-linear, depending on the distribution of the data [21,23,24]. In this study, the scaling of the training data set was carried out using the following equation:

$$P_j^{\text{scaled}} = \frac{2 \times (P_j - P^{\text{lower}})}{P^{\text{upper}} - P^{\text{lower}}} - 1 \tag{3}$$

where P_j^{scaled} and P_j are the scaled and un-scaled values of the training set respectively, P^{upper} and P^{lower} are the upper and lower values of the data set under scaling, respectively. It should be noted that any new input data should be scaled before presented to the network and the corresponding predicted values should be un-scaled before use.

6.3. Training stage of neural network

Different training functions available in MATLAB version 6 [21] were experimented for the current application. The Fletcher–Reeves technique built in MATLAB version 6 [21] proved to be an efficient training function, and therefore, is used to construct the NN model. This training function is one of the conjugate gradient algorithms that start training by searching in the steepest descent direction (negative of the gradient) on the first iteration. A line search is then performed to determine the optimal distance to move along the current search direction. Then the next search direction is determined so that it is conjugate to previous search directions. The general procedures for determining the new search are to combine the new steepest descent direction with the previous search direction. The training parameters of the Fletcher–Reeves algorithm include: the maximum number of iterations, target performance which specifies the tolerance between the neural network prediction and actual output, the maximum run time, the minimum allowed gradient and the selection of the suitable line search technique.

It is recommended when using back-propagation algorithm in MATLAB version 6 [21] that the data set is divided into three sets; training set, validation set and testing set. The training set is used to gradually reduce the ANN error. The error on the validation set is monitored during the training process. When the network begins to over-fit the data, the error on the validation set will typically begin to rise. When the validation set error increases for a specified number of epochs, the training is stopped. The test set is used as a further check for the generalisation of the NN, but do not have any effect on the training. In the present work, training data set comprises 103 data entries, and the remaining data entries (102) are equally divided between the validation and testing sets. The dividing process was carried out randomly between the three sets and each dataset has been statistically examined to ensure that it covers the range of input parameters.

6.4. Identification of neural network architecture

Several architectures of NN models were examined by varying the number of hidden layers, number of neurons in each hidden layer and the training function parameters of Fletcher–Reeves algorithm. The best neural network was identified after a number of trials to have four layers: an input layer of four neurons, first hidden layer of two neurons, second hidden layer of four neurons and an output layer of one neuron as shown in Fig. 4. The four neurons of the input layer represent: outside anchor diameter d_o, the effective embedment depth h_{ef}, the concrete compressive strength f'_c and the edge distance c_1 from the anchor bolt to the concrete edge, measured in the direction of the shear force. The sigmoid function was used to transfer the values of the input layer neurons to the two neurons in the first hidden layer, whereas the linear transfer function was adopted to transfer the values from the first hidden layer to the second hidden layer. The transfer function between the last hidden layer and the output layer was linear. The only neuron of the output layer gives the concrete shear capacity of single anchor bolts.

It should be noted that when only one hidden layer having two neurons connected by the sigmoid transfer function to the input layer was used, the neural network did not give good generalisation of the network (under-fitting), indicating that more neurons are required. However, adding more neurons to the only hidden layer produced over-fitting of the network output. This shows that the non-linearity of the current application is not high. The linear transfer function is then implemented between the input and hidden layers; however, this architecture did not improve the situation. The problem was finally overcome by introducing a second hidden layer with four neurons connected to the first hidden layer by the linear transfer function.

6.5. Evaluation of network performance

The training of the neural network is carried out using the training data set. Testing and monitoring of the developed neural network during the training stage is performed by computing the mean squared error over all training, validation and testing data sets. After each training iteration, the obtained weights are used to predict the corresponding shear capacity to the input parameters of the training, validation and testing data sets. The mean squared error was calculated for each pattern as the difference between the concrete shear capacity obtained from the trained neural network and the corresponding experimental concrete shear capacity. The training process is terminated when any of the following conditions are satisfied: the maximum number

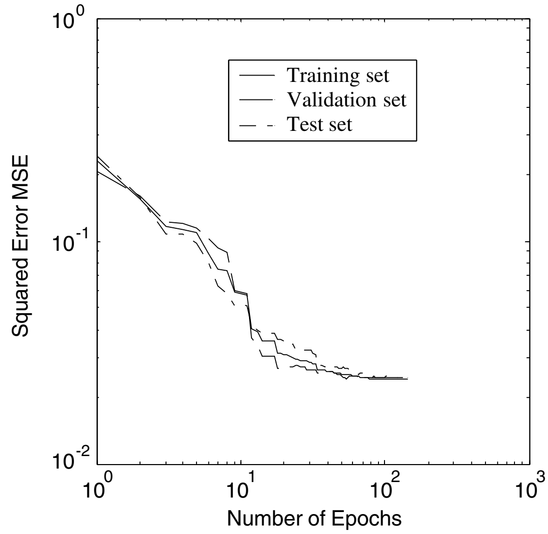


Fig. 5. Training progress of the neural network.

of iterations (epochs) is reached; the performance is minimised to the required target; the performance gradient falls below a minimum value; or the mean squared error of the validation data set starts to rise for a specified number of epochs.

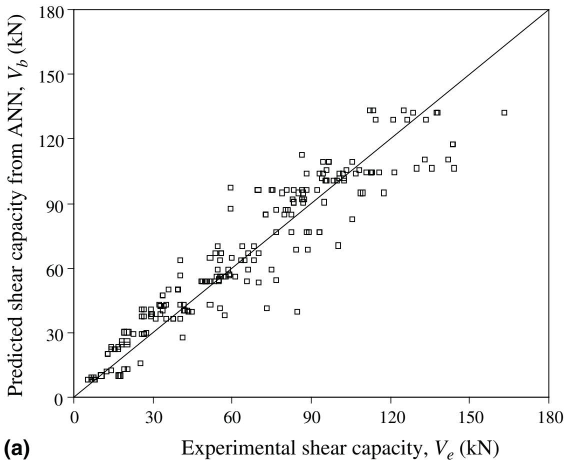
The progress of the training was checked by plotting the training, validation and test mean square errors versus the performed number of epochs, as presented in Fig. 5. The results shown in Fig. 5 are fairly reasonable, since both the test and validation set errors have very similar characteristics, and no significant over-fitting has occurred. Comparisons of the concrete shear capacity of anchors from experiments and those obtained from the trained neural network and the CCD approach are presented in Fig. 6(a) and (b), respectively.

Table 2 gives different statistical parameters estimated to measure the performance of the trained NN and the CCD method. The mean μ and standard deviation σ of the ratios of the experimental concrete shear capacity V_e of anchor bolts to the corresponding NN and CCD values, V_e/V_b^{NN} and V_e/V_b^{CCD}, respectively, are presented in Table 2. The average absolute relative error β in estimating the shear strength was 17.4% with the trained NN and 23.6% with the CCD method, whereas the maximum absolute relative errors, max β, in estimating the shear strength using the trained NN and the CCD method were 61.0% and 87.1%, respectively as given in Table 2. The coefficient R^2 of determination is a measure of the goodness of fitness between the target and the computed output by the trained NN and the CCD method. The coefficients R^2 of determination of the NN and CCD values were 0.886 and 0.768, respectively as indicated in Table 2. These statistical parameters show that the predicted concrete shear capacities of anchor bolts using the trained NN and the CCD method are in good agreement with the experimental results and the predictions obtained from the trained NN are as good as or even better than those obtained from the CCD approach.

Table 2
Statistical parameters for measuring the performance of the trained NN and the CCD method

Method	μ	σ	β%	max β%	R^2
ANN	1.054	0.22	17.4	61.0	0.886
CCD	1.093	0.28	23.6	87.1	0.768

μ and σ = the mean and standard deviation of the ratio between the measured and predicted shear capacities, β = the average absolute relative error in the predicted shear capacities, max β = the maximum absolute relative error in the predicted shear capacities and R^2 = the coefficient of determination.



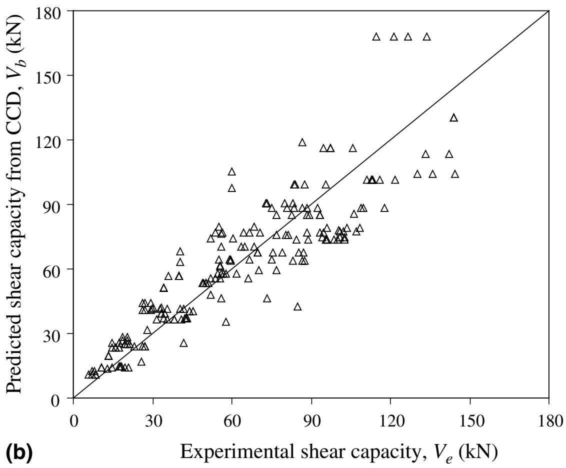


Fig. 6. Comparison of predicted concrete shear capacities using the (a) ANN and (b) CCD versus experiments.

7. Parametric study

The trained neural network is utilised to simulate the effects of the input parameters on the concrete shear capacity of single anchors as given in Figs. 7–10. The predictions obtained from the CCD method (representing the new provisions given in the ACI 318-02 Appendix D [16]) is also presented in Figs. 7–10. Fig. 7 shows the effect of the outside anchor diameter d_o on the concrete shear capacity of anchors having 150 mm embedment depth, installed in concrete of cylinder compressive strength $f_c' = 40$ MPa for different edge distances. Fig. 7 indicates that a small change of the concrete shear capacity is observed when the anchor diameter is increased from 12 mm to 32 mm. This observation agrees well with the 45° concrete cone method, which ignores the effect of the anchor diameter. Fig. 8 presents the influence of the effective embedment depth on the concrete shear capacity of anchors having 22 mm diameter, installed in concrete of 40 MPa com-

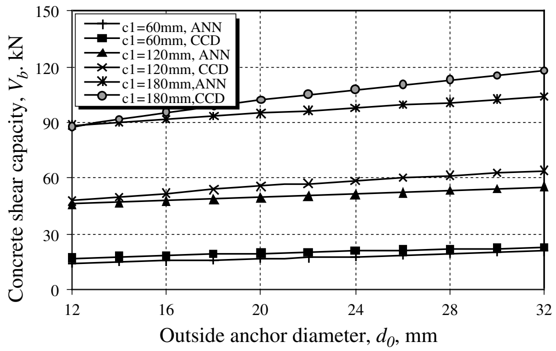


Fig. 7. Effect of outside diameter on the concrete shear capacity of anchor bolts ($h_{ef} = 150$ mm and $f'_c = 40$ MPa).

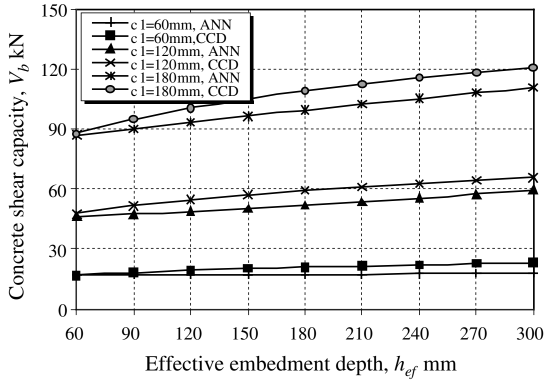


Fig. 8. Effect of effective embedment depth on the concrete shear capacity of anchor bolts ($d_o = 22$ mm and $f'_c = 40$ MPa).

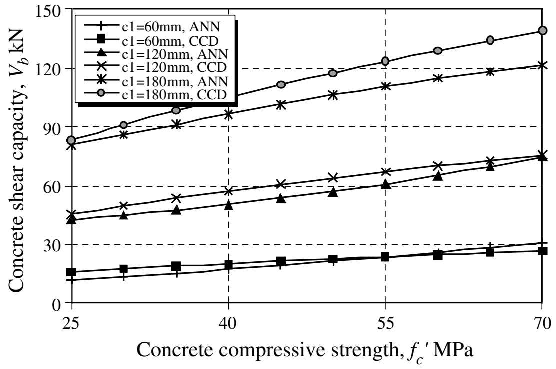


Fig. 9. Effect of concrete compressive strength on the concrete shear capacity of anchor bolts ($d_o = 22$ mm and $h_{ef} = 150$ mm).

pressive strength for different edge distances. As the embedment depth of anchors increases, the concrete shear capacity of anchors slightly increases. In Figs. 7 and 8, the trained neural network predicts less effect of anchor diameter and embedment depth on the concrete

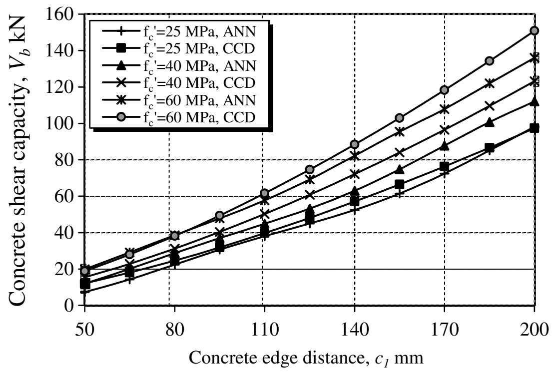


Fig. 10. Effect of edge distance on the concrete shear capacity of anchor bolts ($d_o = 22$ mm and $h_{ef} = 150$ mm).

shear capacity of anchors than the CCD method. Fig. 9 introduces the effect of the concrete compressive strength on the concrete shear capacity of anchors having 22 mm diameter and 150 mm embedment depth for different edge distances. It can be noted that the concrete shear capacity increases non-linearly as the concrete compressive strength increases. Fig. 10 presents the effect of the edge distance on the concrete shear capacity of anchors having 22 mm diameter and 150 mm embedment depth for different concrete compressive strengths. It can be observed that the edge distance of anchors has the most significant effect of all input parameters on the concrete shear capacity of anchor bolts. Figs. 7–10 indicate that the trend predicted by the trained neural network is similar to that obtained from the CCD method. Figs. 7–10 also show that as the concrete shear capacity increases, the CCD predictions become marginally higher than those of the NN ones.

8. Conclusions

This paper demonstrated the possibility of adopting neural networks to predict the concrete shear capacity of anchors. The training of the ANN was achieved using experimental data extracted from the comprehensive worldwide database of mechanical anchors compiled by the ACI committees 349 and 355. The prediction from the trained neural network should be reliable provided that the input data are within the range used in the training set as given in Table 1. The trained ANN predictions conform to the ACI 318-02 Building Code provisions pertaining to anchoring to concrete. Based on the parametric study conducted using the trained ANN, the following conclusions may be drawn:

- The concrete edge distance in the direction of the applied shear has the most influential effect on the concrete shear capacity of anchor bolts.

- Both the embedment depth and diameter of anchor bolts have a small influence on the concrete shear capacity of anchor bolts.
- The concrete shear capacity of anchor bolts is non-linearly affected by the concrete compressive strength.
- Overall, the accuracy of approximation using the CCD method is comparable to that obtained from the trained artificial neural network.

Acknowledgement

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