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ScienceDirect
Journal of the Franklin Institute 344 (2007) 741–756
Journal of The Franklin Institute
www.elsevier.com/locate/jfranklin

Modeling and simulation of shear resistance of R/C beams using artificial neural network

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Received 14 December 2005; accepted 17 December 2005

Abstract

Artificial neural network (ANN) has been used in several engineering application areas including civil engineering. The use of ANN to predict the behavior of reinforced concrete (R/C) members, using the vast amount of experimental data as a test-bed for learning and verification of results, proved to be a viable method for carrying out parametric studies. This paper presents application of ANN for predicting the shear resistance of rectangular R/C beams. Six parameters that influence the shear resistance of beams, mainly shear-span-to-depth ratio, concrete strength, longitudinal reinforcement, shear reinforcement, beam depth and beam width, are used as input for the ANN. A back propagation neural network (BPNN) with different activation functions is used and their results are compared. The sigmoid function with variable threshold is adopted due to its accuracy of prediction. The ANN prediction and the measured experimental values are compared with the shear strength predictions of ACI318-02 and BS8110 codes. A sensitivity study of the parameters that affect shear strength of R/C beams is carried out and the underlying complex nonlinear relationships among these parameters were investigated. Shear response curves and surfaces based on these parameters were generated. It is concluded that ANN can predict, to a great degree of accuracy, the shear resistance of rectangular R/C beams and it is a viable tool for carrying out parametric study of shear behavior of R/C beams.

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doi:10.1016/j.jfranklin.2005.12.005

1. Introduction

Artificial neural networks (ANN) are information processing system and since their inception they have been used in several engineering application areas including civil engineering. There is a great advancement in the field of ANN, both from theoretical and applications points of view. ANN have been used in classification, pattern matching, pattern recognition, optimization and control-related problems [1,2]. In civil engineering, neural networks have been used to solve a wide variety of civil engineering problems [3–8]. Neural network has also been used extensively in the area of structural engineering to solve many problems [7–10]. Most of the problems solved in structural engineering using ANN are prediction of behavior based on given experimental results that are used as a training, testing and verification data. Back-propagation neural networks (BPNN) are the most commonly used type of networks in structural engineering applications where a set of input parameters are mapped through single or several hidden layers, using weights, into output parameters. The relationship between the input parameters and the output parameters is usually nonlinear. Although several activation functions are used to accomplish the mapping process, nevertheless, the sigmoid function and its variations are the most widely used activation function in solving structural engineering problems.

In recent years several researchers used ANN to predict fresh and hardened concrete properties. Bai et al. [11] presented a neural network model that predicts the workability of concrete with cement replacement materials. The results of their neural network model were comparable to experimental results and illustrated how neural networks can be used to accurately predict the workability parameters. Oreta et al. [12] explored the application of neural network in modeling of confined compressive strength and strain of circular concrete columns. Although, the neural network prediction was comparable to some analytical models, however, their study proved the importance of validating the neural network models in simulating physical processes especially when data are limited. In addition, Kasperkiewicz et al. [13], Yeh [14], Guang et al. [15], Lee [16] and Kim et al. [17] presented several neural network models for estimation of concrete strength using concrete mix parameters. The predicted results were very comparable to the measured values. Waszczyszyn et al. [18] used BPNN to solve many structural mechanics problems and concluded that they can be efficiently used in solving hybrid problems of structural mechanics. Hadi [19] also used BPNN to optimize the design of concrete beams and their cost and proved that ANN is more accurate and easy to implement compared to conventional methods. Mohamedzein et al. [20] and Abdalla et al. [21] used neural network for sizing of structural members and for estimating the bill of quantities of reinforced concrete (R/C) buildings, based on preliminary design data.

The application of neural network for prediction of shear strength of R/C beams with and without shear reinforcement has been an area of continuous research that have been addressed by many researchers in recent years. Goh [22] and Sanad et al. [23] used multi-layers BPNN to predict the shear strength of deep beams. Accurate results were obtained. Rajasekaran et al. [24] used sequential learning neural network model for the prediction of ultimate shear strength of R/C deep beams. They used a sequential orthogonal approach to build and train the neural network with a single radial basis function (RBF) neuron and their prediction was sufficiently accurate. Mansour et al. [25] also used multi-layer BPNN to predict the ultimate shear strength of R/C beams with shear reinforcement. They used nine input parameters for the neural network and accurate results were produced within the range of input parameters. Oreta [26] used five input parameters to study the size effect on shear strength of R/C beams without shear reinforcement using BPNN model. The neural network gave accurate result and managed to simulate the effect of beam size on ultimate shear stress at diagonal tension failure. Adhikary et al. [27] used neural network to predict the shear capacity of steel-plated-R/C beams. Their study showed that neural network can simulate the shear behavior of R/C beams with web-bonded steel plate. El-Chabib et al. [28] used ANN to predict the shear capacity of normal and high-strength concrete for slender beams without shear reinforcement. Five input parameters were used and it was found that the neural network model performed very well compared with other formulas. They also proved that shear strength of rectangular R/C beams made up of high-strength concrete (HSC) decreases with the increase of concrete strength as was demonstrated experimentally.

In this study an ANN with back-propagation (BP) is used to predict the shear strength of R/C beams [29]. Six parameters are used as input for the ANN. Several activation functions are used to map the nonlinear relationships among the parameters that influence the shear strength of R/C beams. These parameters are beam depth, beam width, concrete compressive strength, lateral reinforcement, longitudinal reinforcement and shear span-to-depth ratio. Several network architectures with different number of hidden layers and different number of neurons in the hidden layers were tried to reach a reasonable architecture. One hundred and sixty-four experimental data sets for determining the ultimate shear strength are used to train the ANN and 30 data sets are used to test and verify the ANN prediction. A parametric study of shear behavior of R/C beams is carried out and the underlying complex nonlinear relationships among the parameters that affect shear strength were presented as shear response surfaces.

2. Shear strength of reinforced concrete beams

There are several modes of failures in concrete structural elements. Shear failure is one of the most serious and undesirable modes of failure due its severity and brittleness. R/C members resist shear force using several mechanisms. One of these mechanism is the concrete shear strength (V_c). Experimental investigations to predict the shear strength of R/C members have been carried out by several researchers and several empirical formulas, based on experimental results, have been developed. Some of these formulas are used in prominent design codes such as the American Concrete Institute (ACI318-02) [30] and the British Standard code of practice (BS8110) [31]. These formulas are used to predict the shear strength of concrete beams and they are functions of several shear parameters. In this investigation, experimental data conducted to determine the shear strength of rectangular R/C beams were collected and the data are used to train and test the ANN to predict the shear strength of these beams. The developed ANN is then used to carry out parametric study for shear strength based on several shear parameters. For a member subjected to shear and flexure only, the American Concrete Institute (ACI318-02) code formula for calculating the concrete shear strength (in the absence of axial force and web reinforcement) is given by

$$V_c = \left(\frac{\sqrt{f'_c}}{7} + \frac{120}{7} \rho_w \frac{V_u d}{M_u} \right) b_w d \leqslant 0.3 \sqrt{f'_c} b_w d, \tag{1}$$

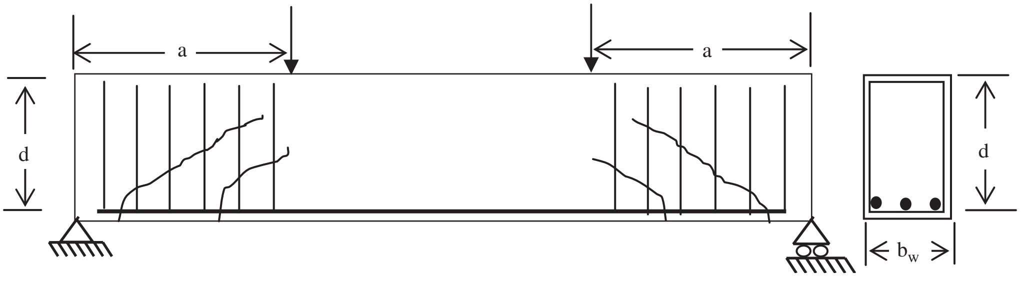

Fig. 1. Rectangular reinforced concrete beam.

where f'_c is the concrete compressive strength in MPa, ρ_w is the longitudinal steel ratio given by $A_s/b_w d$, V_u is the factored shear force, M_u is the factored bending moment occurring simultaneously with V_u at the section considered, b_w is the width of the beam and d is the effective depth of the beam as shown in Fig. 1 and $V_u d/M_u \leqslant 1.0$. The shear resistance of stirrups (shear reinforcement) according to ACI318-02 is given by

$$V_s = A_v f_y(\sin\alpha_s + \cos\alpha_s)d/S, \tag{2}$$

where A_v is the shear reinforcement area, f_y is the yield strength of shear reinforcement, d is the effective depth of the beam, S is the stirrups spacing, α is the stirrups inclination angle and A_v is the shear reinforcement area. For vertical stirrups $\alpha = 90^\circ$, Eq. (2) becomes

$$V_s = \frac{A_v f_y d}{S}. \tag{3}$$

The nominal shear strength of the section is given by

$$V_n = V_c + V_s. \tag{4}$$

The concrete shear strength formula according to the British Standard code of practice (BS8110) is given by

$$V_c = \frac{0.79}{\gamma_m}\left(\frac{100A_s}{bd}\right)^{1/3}\left(\frac{400}{d}\right)^{1/4} \quad \text{for } F_{cu} \leqslant 25, \tag{5}$$

where A_s is the steel area, b is the width of the beam and d is the effective depth of the beam as shown in Fig. 1. γ_m is the partial safety factor $= 1.25$ and $100A_s/bd \leqslant 3$, $1.0 \leqslant 400/d \leqslant 4.0$. For $25 \leqslant F_{cu} \leqslant 40$, Eq. (5) need to be multiplied by a factor $= (F_{cu}/25)^{1/3}$, where F_{cu} is in MPa.

The shear resistance of stirrups (shear reinforcement) according to BS8110 is given by

$$V_s = \frac{0.87 f_y A_v}{bS}. \tag{6}$$

3. Artificial neural network model and training

ANN are information processing systems that are capable of learning complex cause and effect relationships between input and output data. ANN may be characterized as a computational model that is based on parallel distributed processing with particular properties such as the ability to learn, to generalize, to classify and to organize data [32]. There are two major neural network architectures: (1) feed forward; and (2) feed backward. Training of ANN could be supervised or unsupervised. BP feed-forward multi-layer perceptron is used extensively in engineering applications.

A BP network in which each neuron has one output and as many input as the neurons in the previous layer is the most common one. The network input is connected to every neuron in the first hidden layer while each network output is connected to each neuron in the last hidden layer. The network weights were originally set to random values and new values of the network parameters (weights) are computed during the network training phase. The neurons output are calculated using

$$O_i = F\left(\sum_j I_j * W_{ij} + b_i\right), \tag{7}$$

where O_i is the output of the neuron i; I_j are the input of j neurons of the previous layer; W_{ij} are the neuron weights; b_i is the bias for modeling the threshold; and F is the *activation function*. The activation function also known as the *processing element* is the portion of the neural network where all the computing is performed. The activation function maps the input domain (infinite) to an output domain (finite). The range to which most activation functions map their output is either in the interval [0, 1] or the interval $[-1, 1]$. There are several activation functions used over the years, however, the most common activation functions belong to five families as follows [33]: (1) *linear* activation function; (2) *step* activation function; (3) *ramp* activation function; (4) *sigmoid* activation function; and (5) *Gaussian* activation function.

Fig. 2 shows a typical neural network with input, hidden layer, summation part, activation function and output part. The ANN error (E) for a given training pattern i is given by

$$E = \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{m}(O_j^i - T_j^i)^2, \tag{8}$$

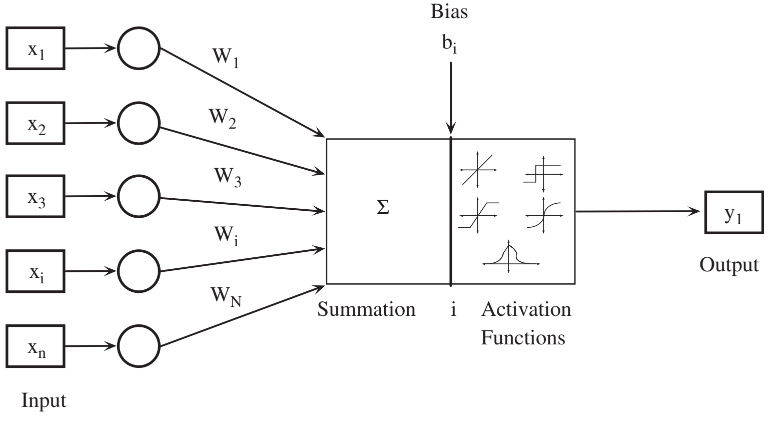

Fig. 2. Neural network.

where O_j^i is the output and T_j^i is the target. Details of neural network theory and applications are given in [1,2].

4. Methodology

There are several programs for design of neural network. Pathia [34], a program for the development and design of neural networks, is used in this investigation to design the network. The number of hidden layers and the number of neuron in each hidden layer are determined based on optimum network configuration. Using Pathia the network architecture has been designed with two hidden layers as shown in Fig. 3. The network has six input parameters and one output parameter, six neurons in the first hidden layer and one neuron in the second hidden layer. The six input parameters are beam depth, beam width, concrete compressive strength, lateral reinforcement, longitudinal reinforcement and shear-span-to-depth ratio. The output parameter is the concrete shear strength V_n.

One hundred and sixty-four experimental data sets have been used to train the ANN and 30 data sets are used to test the ANN. Table 1 shows the range of maximum and minimum values of the training and testing data that is used in this study. Initial random values are used for the weight. After several training sessions the weights of the six neurons of the first hidden layer and the weights of the single neuron of the second hidden layer were calculated.

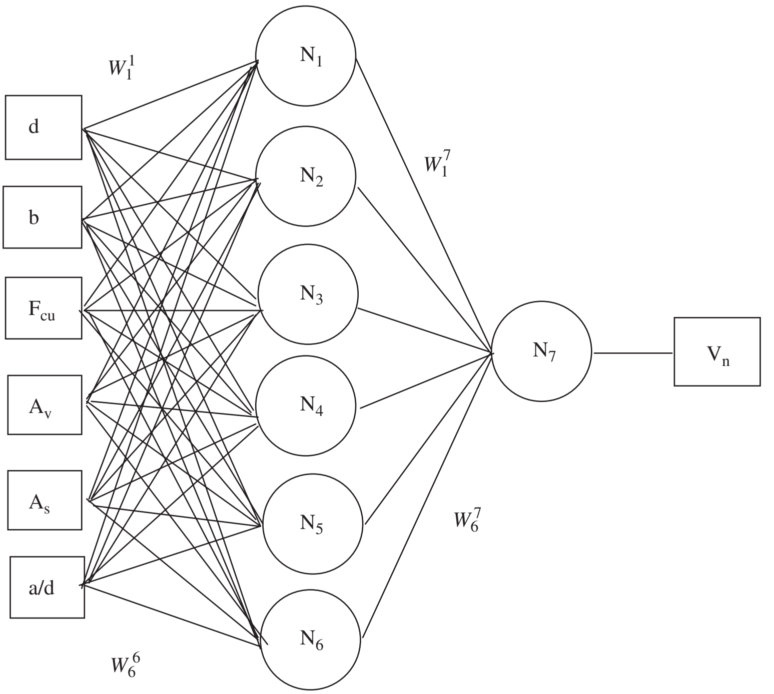

Fig. 3. Neural network architecture.

Table 1
Range of training and testing parameters

Parameter	Training data		Testing data	
	Maximum	Minimum	Maximum	Minimum
b (mm)	200	76.2	200	76.2
d (mm)	374	95	350	95
ρ_w (%)	5.0	0.2	3.95	0.2
ρ_v (%)	1.87	0.0	1.2	0.0
a/d	11.56	2.00	6.29	2.00
f_c (MPa)	73.64	15.30	72.4	22.14
V_n (kN)	330.95	7.34	175	9.88

Table 2
Trial result using different activation functions

Activation function	Mathematical form	Max. error (%)	Min. error (%)	Average error (%)
Sigmoid function + variable threshold (T)	$\frac{1}{1+\exp(-ax+T)}$	15.15	−12.26	−0.43
Sigmoid function	$\frac{1}{1+\exp(-0.5x)}$	50.45	−55.04	1.52
Sigmoid function + constant threshold	$\frac{1}{1+\exp(-x)} - 0.5$	77.91	−119.95	−1.49
Tanh function + variable threshold (T)	$\tanh(x)+T$	122.05	−85.63	−1.53
Tanh function	$\tanh(x)$	85.83	−337.02	−52.15

In this study several activation functions were used. Table 2 summarizes the results of using different activation functions. It is clear that the results of the sigmoid function with variable threshold are more accurate than results of other activation functions. The tanh function shows the worst performance among these activation functions. The result of the sigmoid function with variable threshold is adopted and its result is used for comparison with code predictions and for carrying out parametric study.

5. Results and discussion

After the network was trained using 164 data sets, it was then tested using 30 data sets for verification of results. The 30 test data sets are used to predict the shear strength using ACI318-02 and BS8110 formulas. Table 3 shows the summary of the result of the ratio of prediction of ANN, BS8110 and ACI318 to that of the measured values of the 30 test data sets. The ANN prediction is clearly better than the prediction of BS8110 and ACI318. It is shown in Table 3 that 63.3% of ANN predictions are within 5% of the measured values compared to only 10% of BS8110 and ACI318 are within 5% of the measured values. Also, 96% of the ANN predictions are within 15% of the measured values while 26.7% of BS8110 and 23.3% of ACI318 are within 15% of the measured values. Although some

Table 3
Ratio of predicted shear strength to measured values

Parameter	ANN	BS8110	ACI318
Maximum value	1.15	1.33	1.41
Minimum value	0.88	0.31	0.36
Standard deviation	0.06	0.26	0.25
Absolute mean	0.98	0.71	0.78
Coefficient of variation	6.11	36.05	32.66
Data with absolute error less than 5%	63.33%	10%	10%
Data with absolute error less than 10%	86.67%	10%	16.67%
Data with absolute error less than 15%	96.67%	26.67%	23.33%

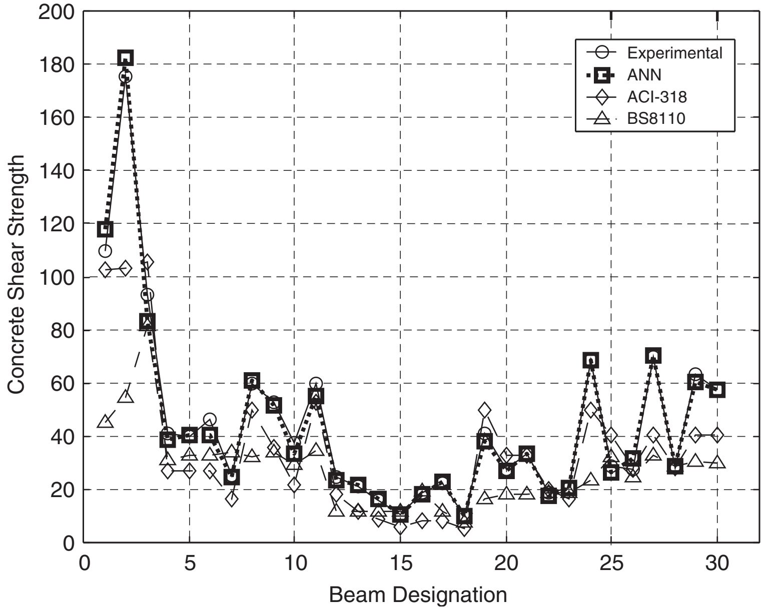

Fig. 4. Comparison of shear strength predictions and experimental results.

error of 15% is shown in some cases, however, in most cases the ANN prediction is very comparable with the experimental result. The absolute mean of the ratio of predicted to measured values as given by the ANN is 0.98 with a standard deviation of 0.06 and coefficient of variation of 6.11%. While the absolute mean of the ratio of predicted to measured values as given by BS8110 and ACI318 are 0.71 and 0.78, respectively, with standard deviations of 0.26 and 0.25 and coefficients of variations of 36.1% and 32.7%, respectively. The relationships between experimental, ANN, ACI318 and BS8110 of the 30 test data are shown in Fig. 4. It is not surprising that the ACI318 code and BS8110 predictions were conservative compared to the experimental results. It is obvious also that

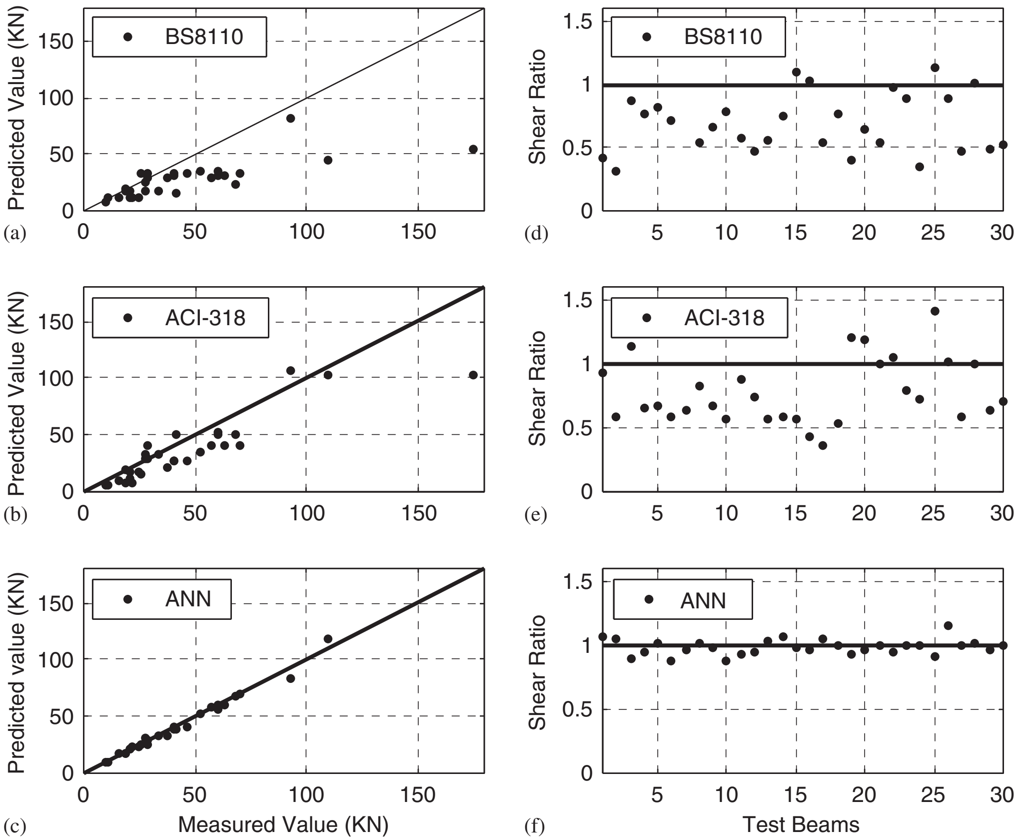

Fig. 5. Performance of shear strength predictions.

the ANN values are very comparable with the experimental results within the range of applicable data.

Fig. 5a–c shows the prediction of shear strength of the test data as given by BS8110, ACI318 and ANN as compared to the line of equality. It is clear that the performance of ANN is much better than that of the ACI318 and BS8110. At low values of shear strength all prediction methods tend to have values close to each other. At higher values of shear strength, ACI318 and BS8110 tend to underestimate the shear strength with exception of few points. Nevertheless, ACI318 and BS8110 predictions show somewhat similar trend. ANN predictions on the other hand are more consistent. This is clearly depicted in Fig. 6 where almost all points of ANN lie within plus or minus 15% of the equality line. Fig. 5d–f shows the scattering of the prediction ratios of ACI318, BS8110 and ANN. As shown in these figures, ANN prediction clutters around unity while ACI318 and BS8110 are more scattered and mainly under the unity line indicating that they predominantly underestimate the shear strength.

Fig. 6 shows the summary of predictions of ANN, ACI318 and BS8110 as compared to experimental measured values. It is obvious that almost all ANN (more than 96%) predictions lie between ±15%. Predictions of ACI318 and BS8110 tend to underestimate

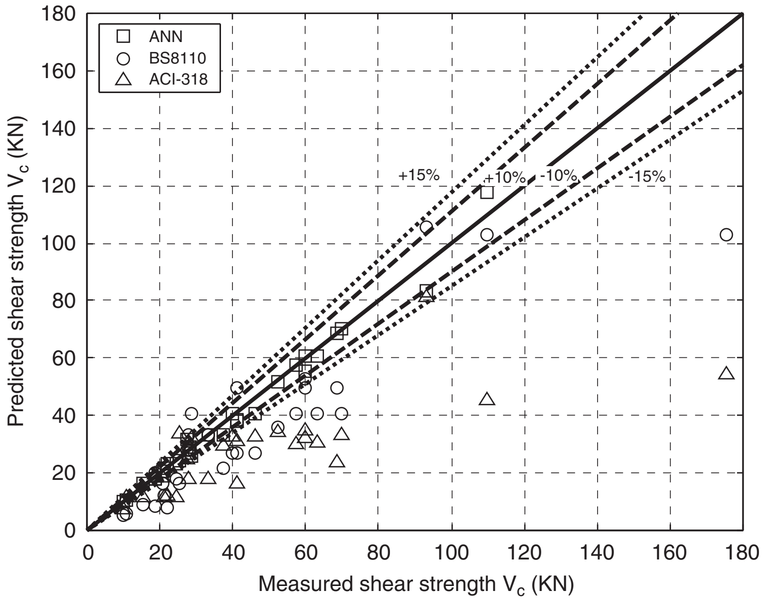

Fig. 6. Deviation of shear strength predictions from experimental results.

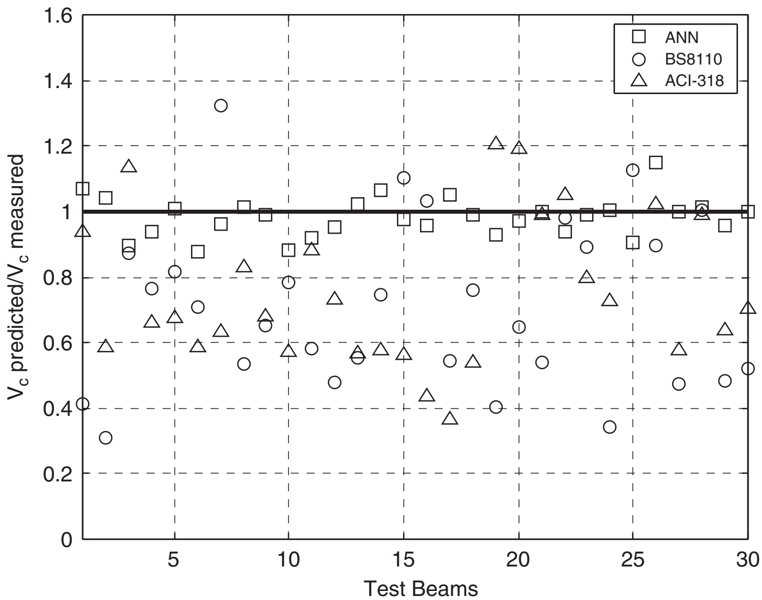

Fig. 7. Summary of shear strength performance of ANN, ACI318 and BS8110.

the shear strength in most of the cases of the test data where only around 25% of the test data fall within ±15% of the measured shear strength. Fig. 7 shows the scattering of the ratios of the shear strength predictions of ANN, ACI318 and BS8110.

6. Parametric studies and sensitivity analysis

It is clear that ANN is capable of predicting shear strength of rectangular concrete beams accurately for data set it was not trained for, however, within the data range of applicability of the network. Therefore, it can be used for parametric study in which the parameters affecting shear strength of R/C beams can be varied and the effect can be studied. In this investigation a parametric study was carried out in which the parameters that influence the shear strength of rectangular R/C beams are varied to study their effect in the shear strength.

6.1. *Effect of shear-span-to-depth ratio*

Fig. 8a shows the ANN prediction of variation of shear strength and shear-span-to-depth ratio for a rectangular beam with $b = 150\,\text{mm}$, $d = 300\,\text{mm}$ and $f_c = 25\,\text{MPa}$ and with different values of longitudinal reinforcement ratios. As expected, the shear strength decreases with the increase in shear-span-to-depth ratio (a/d). Fig. 8b shows the ANN

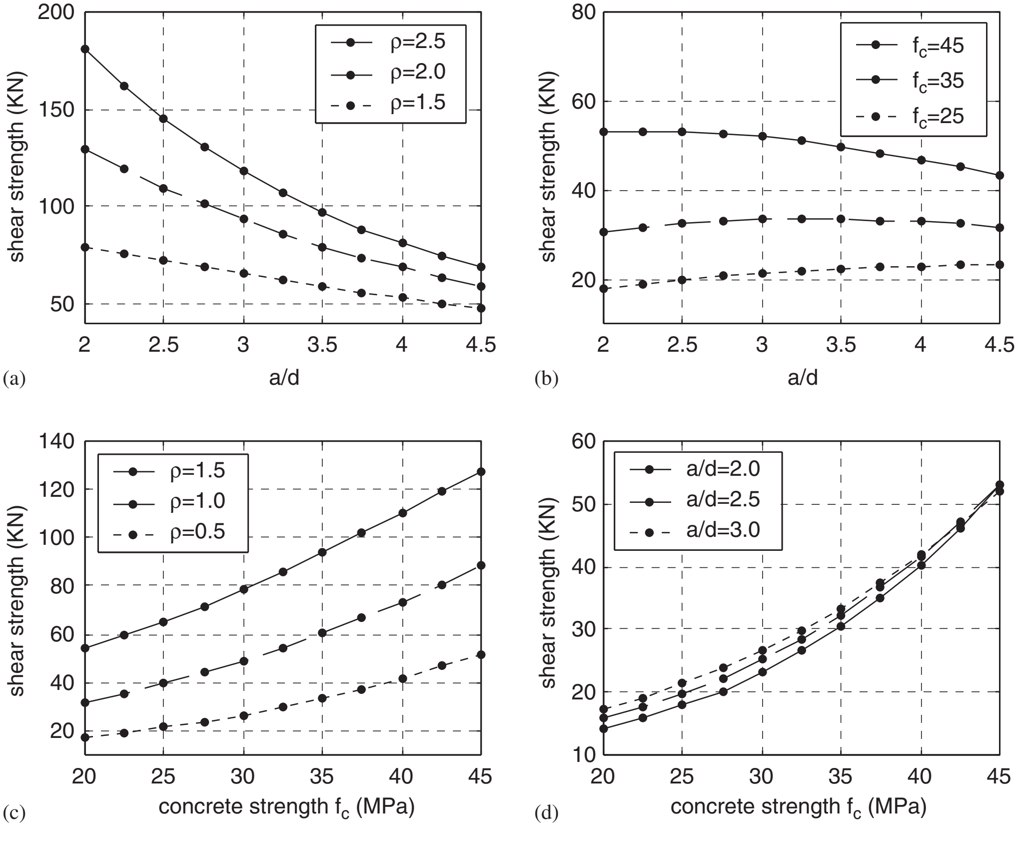

Fig. 8. Variation of shear strength with a/d, ρ and f_c. (a) $b = 150\,\text{mm}$, $d = 300\,\text{mm}$, $f_c = 25\,\text{KN}$; (b) $b = 150\,\text{mm}$, $d = 300\,\text{mm}$, $\rho = 0.5\%$; (c) $b = 150\,\text{mm}$, $d = 300\,\text{mm}$, $a/d = 3.0$; (d) $b = 150\,\text{mm}$, $d = 300\,\text{mm}$, $\rho = 0.5\%$.

prediction of the variation of shear strength and shear-span-to-depth ratio for different values of concrete strength for the same beam. For high- strength concrete, strength decreases with increase in span-to-depth ratio. However, the decrease is more evident for slender beams with $a/d > 2.5$.

6.2. Effect of concrete strength

Fig. 8c shows the ANN prediction of the variation of shear strength and concrete strength (f_c) for different values of longitudinal reinforcement ratios. For the same concrete strength, shear strength increases with the increase of concrete strength as expected for the normal strength concrete. Fig. 8d shows the variation of shear strength and concrete strength for different shear-span-to-depth ratios. It is observed that for the same a/d, shear strength increases with concrete strength.

Fig. 9a–d shows the generalization of the ANN prediction of shear strength of rectangular R/C beams as function of shear-span-to-depth ratio (a/d), concrete strength (f_c) and longitudinal reinforcement ratio (ρ). The shear planes give an inside on how different parameters affect the shear strength of rectangular R/C building.

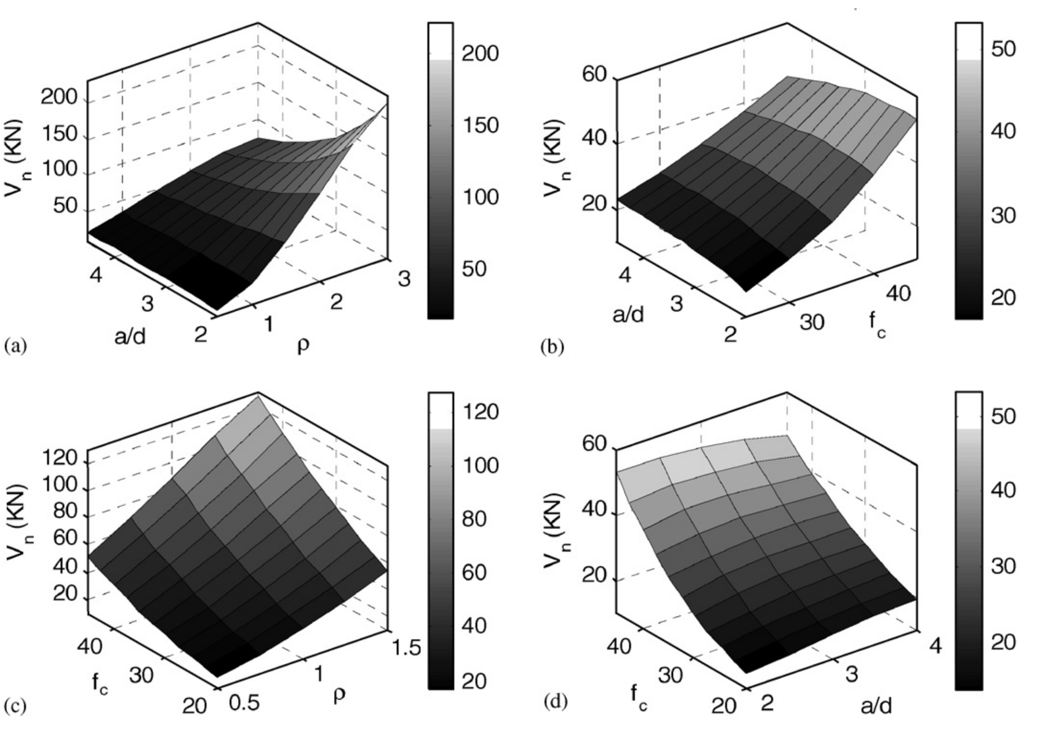

Fig. 9. Shear strength planes as functions of a/d, ρ and f_c. (a) $b = 150$ mm, $d = 300$ mm, $f_c = 25$ KN; (b) $b = 150$ mm, $d = 300$ mm, $\rho = 0.5\%$; (c) $b = 150$ mm, $d = 300$ mm, $a/d = 3.0$; (d) $b = 150$ mm, $d = 300$ mm, $\rho = 0.5\%$.

6.3. Effect of longitudinal reinforcement

Fig. 10a shows the variation of shear strength and longitudinal reinforcement ratio (ρ) for different values of concrete strength (f_c). For the same concrete strength, shear strength increases with longitudinal reinforcement until a certain ratio level then it starts to decrease. This ratio level depends on the concrete strength as shown in Fig. 10a. Fig. 10b shows the variation of shear strength and reinforcement ratio for different values of shear-span-to-depth ratio. It is observed that at low longitudinal reinforcement ratio, the shear-span-to-depth ratio has no effect in the shear strength. As the longitudinal reinforcement ratio increases the shear strength increases with the decrease in shear span-to-depth ratio as calculated before.

6.4. Effect of beam width and depth

Fig. 10c shows the variation of shear strength and beam width (b) for different values of shear-span-to-depth ratio (a/d). Fig. 10d shows the variation of shear strength and beam

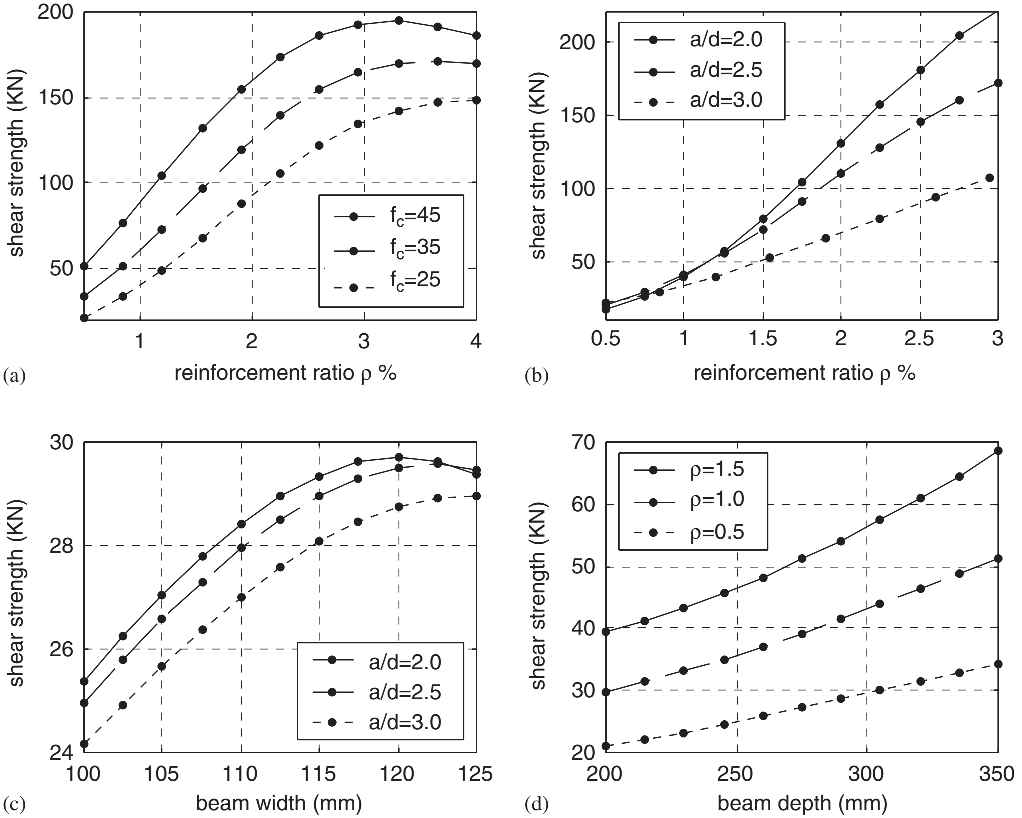

Fig. 10. Variation of shear strength with ρ, a/d, f_c, b and d. (a) $b = 150$ mm, $d = 300$ mm, $a/d = 3.0$; (b) $b = 120$ mm, $d = 250$ mm, $f_c = 25$; (c) $d = 300$ mm, $\rho = 0.5\%$, $f_c = 25$ MPa; (d) $b = 120$ mm, $a/d = 2.5$, $f_c = 25$ MPa.

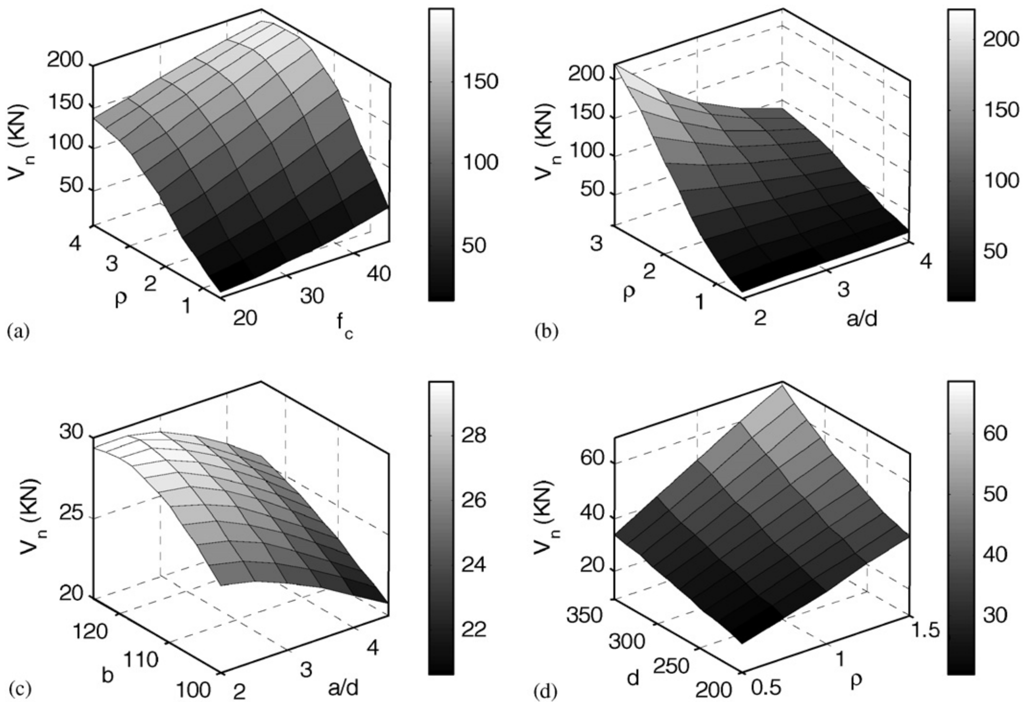

Fig. 11. Shear strength planes as functions of ρ, a/d, f_c, b and d. (a) $b = 150$ mm, $d = 300$ mm, $a/d = 3$; (b) $b = 120$ mm, $d = 250$ mm, $f_c = 25$ MPa; (c) $d = 300$ mm, $\rho = 0.5\%$, $f_c = 25$ MPa; (d) $b = 120$ mm, $a/d = 2.5$, $f_c = 25$ MPa.

depth (d) for different values of longitudinal reinforcement ratio (a/d). As indicated, as the depth increases the shear strength of the beam increases.

Fig. 11a–d shows the generalization of the ANN prediction of shear strength of rectangular R/C beams as function of shear-span-to-depth ratio (a/d), concrete strength (f_c), longitudinal reinforcement ratio (ρ), beam depth (d) and beam with (b). As previously indicated, the shear planes give an inside on how different parameters affect the shear strength of rectangular R/C building.

7. Summary and Conclusions

In this investigation, application of ANN for predicting the shear resistance of rectangular R/C beams was carried out. A back-propagation neural network (BPNN) is used. The ANN prediction and the measured experimental values are compared with the shear strength predictions of ACI318-02 and BS8110 codes. A sensitivity study of the parameters that affect shear strength of R/C beams was carried out. It can be concluded from this study that:

- ANN can accurately model the complex and nonlinear relationship among parameters of physical phenomenon such as those affecting the shear strength of rectangular R/C beams. The ANN prediction is accurate provided that it is within the range of input data used for training the network.

- ANN predictions of shear strength are more accurate than the shear strength predictions of ACI318 and BS8110. It has been shown that the ratio of ANN predictions over the measured values has absolute mean $\mu = 0.98$, standard deviation $\sigma = 0.06$ and COV $= 6.11\%$ as compared to ACI318 and BS8110 predictions ratios that have absolute means of $\mu = 0.71$; $\mu = 0.78$, standard deviations $\sigma = 0.26$; $\sigma = 0.25$, and COV $= 36.1\%$; COV $= 32.7\%$, respectively.
- ANN is an effective and inexpensive tool for carrying out parametric study among several parameters that affect physical phenomenon in engineering as demonstrated for the case of shear strength of rectangular R/C beams.
- BPNN with sigmoid function can be used to predict the shear strength of R/C beam accurately.

Acknowledgment

This work is based on data collected by Ashraf, Hatim, Khalid and Ramie. Their effort is greatly appreciated.

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