APPLICATION OF NEURAL NETWORK MODEL FOR THE PREDICTION OF SHEAR STRENGTH OF REINFORCED CONCRETE BEAMS

Irshad Ahmad[*], Attaullah Shah[†], Akhter Naeem Khan[‡]

Abstract: This paper evaluates the feasibility of using an Artificial Neural Network (ANN) model for estimating the nominal shear capacity of Reinforced Concrete (RC) beams against diagonal shear failure subjected to shear and flexure. A feedforward back-propagation ANN model was developed utilizing 622 experimental data points of RC beams, which include 111 deep beams data and 20 beams tested for low longitudinal steel ratios. The ANN model was trained on 70% of the data and then it was validated using the remaining 30% data (new data were not used for training). The trained ANN model was compared with three existing approaches, including the American Concrete Institute (ACI) code. The ANN model predictions when compared to the experimental data were very favorable, regarding also the other approaches. The prediction of ANN model was also checked for size effect and deep beams separately. The ANN model was found to be very robust in all situations. The safe form of ANN model was also derived and compared with the design equations of the three methods.

Key words: *Neural network, shear, beam, concrete, deep beams, size effect*

Received: September 2, 2009
Revised and accepted: September 15, 2010

1. Introduction

Despite several decades of study, the diagonal shear failure of reinforced concrete beams is a complex problem that has not been solved to complete satisfaction.

[*]Irshad Ahmad
Department of Civil Engineering, NWFP University of Engineering and Technology, Peshawar-Pakistan
[†]Attaullah Shah
Project Director Allama Iqbal Open University Islamabad, Pakistan
[‡]Akhter Naeem Khan
Department of Civil Engineering, NWFP University of Engineering and Technology, Peshawar-Pakistan

Proposed theories vary radically from the simple 45° truss model to the very complex non-linear fracture mechanics. Yet nearly all the resulting design procedures are empirical or semi-empirical at best and are obtained by a regression fit through experimental results.

Neural networks are an information processing technique which is based on the analogy of human nervous system comprising of neurons used to solve problems by learning. The neural network is configured for a specific application, which is often called training. The results and computations of the neural models depend on the basic training of neurons [Adhikary and Mutsuyosh, 2006].

The shear strength of RC beams involves a number of parameters and the research on the shear strength of RC beams is still an active area in the contemporary research, the aim of which is to explore more rational and exact solutions. However, many researchers have used ANN models to study the shear strength of RC beams.

Hadi (2002) used the application of ANN for the optimization of RC beams section in terms of its geometry, concrete strength and reinforcing steel.

Kumar and Barai (2009) used the neural network modeling for predicting shear strength of corbels. They reported that the proposed model based on back propagation networks with the Lavenberg–Marquardt algorithm has given very reasonable results when compared with the actual tests results from the test database.

Saridemir (2009) used the ANN for prediction of the compressive strength of concrete using metakaolin and silica fumes at various ages of concrete. A multilayer feed-forward neural networks model was used involving eight input parameters, i.e. age of specimen, cement, metakaolin (MK), silica fume (SF), water, sand, aggregate and superplasticizer. The results of the proposed training, when compared with actual compressive strengths of concrete, were found very close to each other.

Oreta (2004) studied the size effect on the shear strength of RC beams with the help of neural network model. He used five input models comprising concrete compressive strength, beam width, effective depth, shear span to depth ratio (a/d) and longitudinal steel ratio, and five hidden layer nodes to calculate the ultimate shear of RC beams without shear reinforcement. The comparison of results of the model with the actual test data showed versatility of the ANN for predicting the size effect on the shear strength of RC beams.

Mansour et al. (2004) developed an ANN model for shear strength of RC beams and applied it to the test data of 176 beams. Nine input parameters were used in the model – they included cylinder concrete compressive strength, yield strength of the longitudinal and transverse reinforcing bars, shear-span-to-effective-depth ratio, span-to-effective-depth ratio, beam cross-sectional dimensions, and longitudinal and transverse reinforcement ratios.

They reported that the ANN has strong potential for predicting the shear strength of RC beams.

The literature review of the application of ANN model for the parametric study of various properties of structural concrete in the fresh and hardened form shows that neural networks provide an intelligent and versatile system for predicting the shear strength of RC beams.

In this paper, the Artificial Neural Network (ANN) technique was utilized in order to evaluate the shear capacity against diagonal shear failure of reinforced concrete beams. The input parameters to the ANN model include: longitudinal tensile steel ratio (ρ), distance from extreme compression fiber to centroid of tension reinforcement (d), ratio of shear span (a) to d, i.e. (a/d), maximum size of aggregate (d_a), compressive strength of concrete (f_c'), web width of beam (b_w), and yield force in stirrups (V_s). The output result of the ANN model is the nominal shear load capacity (V_c) at failure. Although it has been recognized that the presence of stirrups has some beneficial effects on magnitude of V_c, this effect is neglected in the current code specifications, i.e. V_c is taken to be the same as in a beam with no stirrups. Preliminary studies on input parameters selection showed that the ANN model developed without considering the effect of b_w and V_s was inferior to the one described in this study, which takes account of the contribution of b_w and V_s to nominal shear load capacity, V_c. The data used by the ANN model covering all the parameters over a wider range of their variability was obtained from Bazant and Sun 1987, and was supplemented by tests results of Ahmad et al. 2000 and Ghannoum 1998.

The nominal shear load at failure (V_c) of reinforced concrete beam predicted by using the ANN model was compared with the results of equations proposed by Bazant and Sun (1987), ACI-318 – 2008, and Zsutty (1971). These formulas are given in Appendix 2. Based on the values of the coefficient of variation and the correlation coefficient calculated for the predicted values of V_c in relation to the actual test values of V_c for all four methods, the ANN method of predicting nominal shear load at failure was superior to all other three methods. In addition, the proposed ANN method can be implemented in a simple hand calculator to work out V_c.

2. Artificial Neural Network (ANN) Model

The artificial Neural Network (ANN) simulates, in a simplified way, the activities of the human brain in order to learn from examples. ANNs consist of highly interconnected processing units called nodes (neurons) that map a complex input pattern with a complex output pattern (Dowla, F. U. and Rogers, L. L. (1995), Hagan et al. (1996)). In this research, we used the Levenberg–Marquardt back-propagation algorithm, which is one of the fastest methods available for training moderate-sized feed-forward neural networks – see Hagan *et al* (1996). The theory and implementation of the Levenberg-Marquardt algorithm is given in detail by More (1977).

The architecture of ANN model developed in this study is shown in Fig. 1. It consists of an input layer of seven input neurons, a hidden layer of seven neurons, and an output layer consisting of one output neuron. The links between the neurons represent the weight and bias connections.

2.1 Design of ANN

The design of a neural network may proceed as follows:

1. First, an appropriate architecture is selected for the neural network model. The ANN model developed in this study consists of an input layer, a hidden

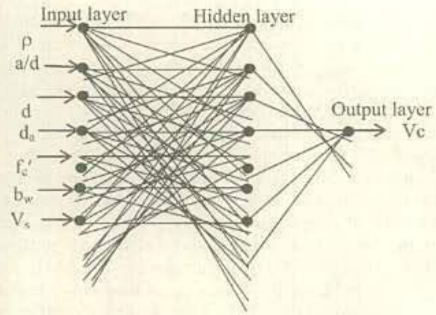

Fig. 1 *Artificial Neural Network Architecture.*

layer, and an output layer. The inputs to ANN model are ρ, a/d, d, d_a, f_c', b_w, and V_s. The input layer consists of nodes (neurons) equal in number to the input parameters. In this case, the input layer of ANN model therefore consists of seven input neurons. The output of the ANN models is the nominal shear load at failure V_c, and therefore each one has only one output neuron in the output layer. The output neuron is assigned a tan-sigmoid transfer function (hyperbolic tangent). The function of hidden neurons is to intervene between the external input and the network output in a useful manner. By adding one or more hidden layers, the network is enabled to extract higher-order statistics. A three-layer network (i.e. input layer, one hidden layer, and output layer) with sufficient neurons is capable (theoretically) of representing any mapping. In this study, a log-sigmoid transfer function is used in the hidden neurons. An optimum number of hidden neurons is selected, i.e.seven in this case.

2. Second, a subset of examples is then used to train the network with the help of a suitable algorithm. In this study, the network is supplied with 70% of the total data for training, and the remaining 30% is reserved for testing the performance of the trained ANN (step 3 below). The network adjusts, using the Levenberg–Marquardt back-propagation algorithm, the connection weights and bias in order to reduce the error between the target and the corresponding network output.

3. Third, the prediction performance of the trained network is tested with data not seen before (30% of the total data in this study). The network predicts the output using the connection weights and biases established in the training phase.

The number of neurons in the hidden layer was determined by training several networks with different numbers of hidden neurons and comparing the predicted

Data Type	Statistical Properties	Input and Output Parameters							
		ρ	a/d	d (mm)	d_a (mm)	f'_c (N/mm^2)	b_w (mm)	V_s (N)	V_c (N)
Complete Data	Maximum	0.066	8.7	1199.9	38.1	101.825	612.1	158910	585357
	Minimum	0.002	1.0	65.0	2.5	6.068	50.0	0	7157
	Range	0.065	7.7	1134.9	35.6	95.758	562.1	158910	578200
	Mean	0.022	3.4	311.2	19.3	31.523	180.6	9671	97323
	Std Dev.	0.012	1.3	151.0	5.3	13.693	72.6	23472	77497
Training Data	Maximum	0.066	8.7	1199.9	38.1	101.825	612.1	158910	585357
	Minimum	0.002	1.0	65.0	2.5	6.068	50.0	0	7157
	Range	0.065	7.7	1134.9	35.6	95.758	562.1	158910	578200
	Mean	0.022	3.4	319.1	19.6	31.205	182.1	11195	103741
	Std Dev.	0.012	1.3	159.0	5.2	13.561	71.7	24543	82165
Testing Data	Maximum	0.050	8.5	1094.7	30.0	81.444	611.1	152573	337399
	Minimum	0.003	1.0	65.0	2.5	11.997	59.9	0	8972
	Range	0.048	7.5	1029.7	27.4	69.446	551.2	152573	328427
	mean	0.022	3.4	293.0	18.6	32.252	176.9	6181	82617
	Std Dev.	0.012	1.2	129.5	5.5	13.999	74.9	20446	63349

Tab. II *Statistical properties of complete, training, and testing data.*

results with the desired output. In this study, five to ten hidden neurons were considered for the ANN model. The optimum number of neurons was found to be seven; this number avoids underfitting, i.e. large training and testing errors, and prevents overfitting, i.e. a low training error but a high testing error.

2.2 Database for training and testing of the ANN model

The data used for training and testing of the ANN model developed in this study were obtained from the database compiled by Bazant and Sun (1987), test results of Ahmad et al. (2000) and Ghannoum (1998). The details of the data used for training and testing of the ANN model are given in Tab. I. Seventy percent (70%) of the available data was used for training and 30% was reserved for testing. The data were divided in this way to give comparable statistical properties for training and testing (Tab. II).

References	Data Points	Total Data	Training Data Points (70 %)	Testing Data Points (30%)
Bazant and Sun (1987)	578 (incl. 126 beams with stirrup reinforcement	622	433 (incl. 101 beams with stirrup, and 79 beams with a/d<2.5)	189 (incl. 25 beams with stirrup, and 32 beams with a/d<2.5)
Ahmad et al. (2000)	20			
Ghannoum W. (1998)	24			

Tab. I *Sources of data.*

2.3 Scaling of training data

Preprocessing of the training data is performed so that the processed data are in the range of −1 to +1. In this study, the training data sets (inputs and targets outputs) are normalized (preprocessed) according to

$$\mathbf{Pn} = 2 \times \frac{(\mathbf{P} - \mathbf{minP})}{(\mathbf{maxP} - \mathbf{minP})} - 1 \tag{1}$$

$$\mathbf{Tn} = 2 \times \frac{(\mathbf{T} - \mathbf{minT})}{(\mathbf{maxT} - \mathbf{minT})} - 1, \tag{2}$$

where $\mathbf{P}$ = matrix of the input vectors; $\mathbf{T}$ = matrix of the output vectors; $\mathbf{Pn}$ = matrix of normalized input vectors; $\mathbf{Tn}$ = matrix of normalized target output vectors; $\mathbf{minP}$ = vector containing minimum values of the original input; $\mathbf{maxP}$ = vector containing maximum values of the original input; $\mathbf{minT}$ = vector containing the minimum value of the target output (i.e. minimum of nominal shear load V_c); $\mathbf{maxT}$ = vector containing the maximum value of the target output (i.e. maximum of nominal shear load V_c). The normalized data were then used to train the neural network. The data from the output neuron have to be post-processed and be converted back into unnormalized units to get actual V_c value according to

$$\mathbf{T} = 0.5 \times (\mathbf{Tn} + 1)(\mathbf{maxT} - \mathbf{minT}) + \mathbf{minT}. \tag{3}$$

The preprocessing and post-processing parameters are given in Tab. III.

Input and Output Parameters	Minimum Value	Maximum Value
ρ	0.0017	0.0662
a/d	0.9788	8.67
d (mm)	65	1199.9
d_a (mm)	2.54	38.1
$f_c{'}$ (N/mm^2)	6.067	101.817
b_w (mm)	50	612.1
V_s (N)	0	158896.8
V_c(N)	7156.8	585356.8

Tab. III *Preprocessing and post-processing parameters for the artificial neural network model.*

2.4 ANN training

The training was carried out until the average sum of squared error over all the training patterns was minimized. This occurred after about 2,000 cycles of training. The weight and bias matrices obtained after the training phase of ANN are $\mathbf{W}_1$ = weight matrix representing connection weights between the input layer neurons and hidden layer; $\mathbf{W}_2$ = weight matrix representing connection weights between the hidden layer neurons and the output neuron; $\mathbf{B}_1$ = bias vector for the hidden layer neurons; $\mathbf{B}_2$ = bias vector for the output layer neuron. The weight and bias matrices are given in Appendix 3.

2.5 Procedure for estimating nominal shear load capacity using the ANN model

The ANN model described in this paper can be used to predict the nominal shear load capacity of reinforced concrete beams. The procedure can easily be programmed in a computer, or performed using a calculator capable of performing simple matrix operations. The input data are first preprocessed according to Equation 1 in order to get normalized input vector **Pn**.

The nominal shear load capacity is then obtained through the network as follows:

$$\mathbf{Tn} = tanh[\mathbf{W}_2 x\{log\text{-}sig(\mathbf{W}_1 x\mathbf{Pn} + \mathbf{B}_1)\} + \mathbf{B}_2], \tag{4}$$

where **Tn** = matrix of normalized output vector and

$$log - sig(x) = \frac{1}{1 + exp(-x)}. \tag{5}$$

The normalized output **Tn** is then unnormalized using Equation 3 to obtain V_c. An example calculation is given in the Appendix 1.

3. ANN Model Prediction and Comparison with Other Methods

3.1 Mean nominal shear load capacity

In order to evaluate the capability of the ANN model, the model was presented with new data, other than the basic training data, in order to calculate V_c. The predicted values of shear load capacity by the ANN model were compared with Bazant and Sun (1987), ACI 2002, and Zsutty's (1971) equations. Figs. 2, 3, 4 and 5 depict the scatter of the ratio of calculated concrete shear load capacity (Vcc) to measured concrete shear load capacity (Vcm) versus Vcm, respectively, for the ANN model, Bazant & Sun, ACI, and Zsutty's equations. The coefficients of variation (cv) of the ratio Vcc to Vcm with reference to unity as mean are given in Tab. IV for all methods. It is shown that the shear load capacity V_c predicted by the ANN for the testing data is the least, i.e. 17.3 %, when compared to the other three methods. Figs. 6, 7, 8 and 9 plot the Vcc against Vcm for testing and training data for all four methods, namely ANN, Bazant and Sun (1987), ACI (2002), and Zsutty's (1971) equation. For the purpose of comparison, the squared correlation coefficient R^2 is defined as

$$R^2 = 1 - \frac{SSE}{SSTO}, \tag{6}$$

where SSTO is the sum of squared differences between Vcm and mean value of Vcm, and SSE is the sum of squared differences between Vcm and the Vcc assuming a 45° regressed line between Vcm and Vcc. Based on this definition, R^2 can take both positive or negative values. The correlation coefficient R is the square root of R^2. The R values are given in Tab. IV. The correlation coefficient for the ANN model is the highest, i.e. 0.976, for testing data.

Method	Testing Data		Training Data		Complete Data	
	cv (%)	R	cv (%)	R	cv (%)	R
ANN	17.3	0.976	17.1	0.987	17.1	0.984
Bazant and Sun	19.2	0.932	19.4	0.948	19.3	0.944
ACI	37.1	0.016	42.5	0.450	40.9	0.390
Zsutty	21.6	0.847	22.8	0.896	22.4	0.883

Tab. IV *Comparison of results of different methods.*

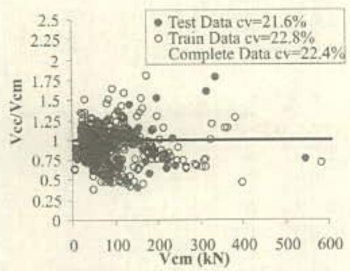

Fig. 5 *Zsutty's equation prediction.*

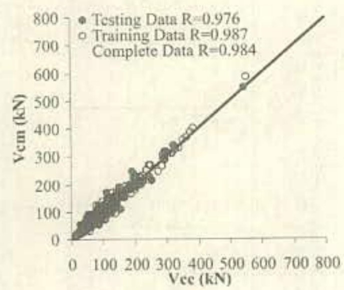

Fig. 6 *Scatter of Vcc by the ANN model.*

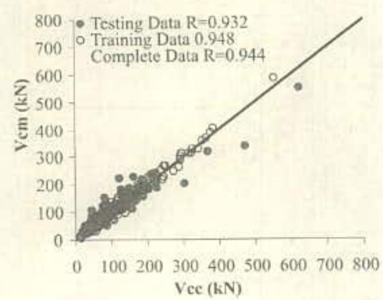

Fig. 7 *Scatter of Vcc by Bazant and Sun equation.*

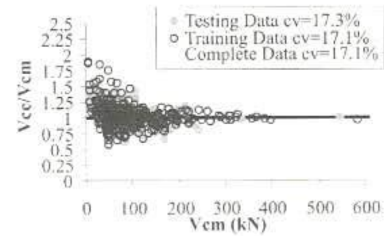

Fig. 2 *The ANN model prediction.*

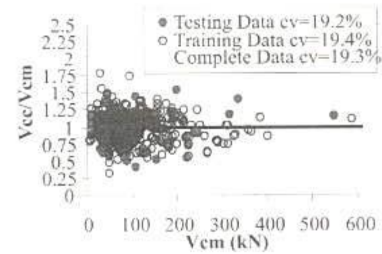

Fig. 3 *Bazant and Sun equation prediction.*

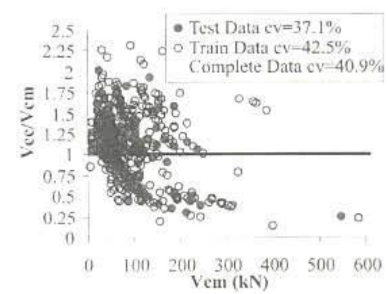

Fig. 4 *ACI equation prediction.*

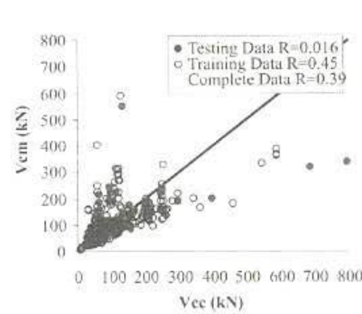

Fig. 8 *Scatter of Vcc by ACI equation.*

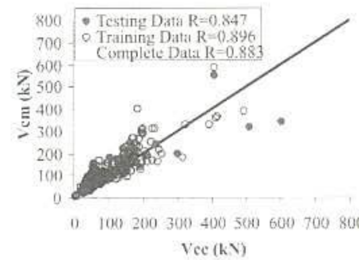

Fig. 9 *Scatter of Vcc by Zsutty's equation.*

3.2 Size effect

The size effect has a pronounced influence on the behavior of concrete beams. Concrete shear capacity may not increase in proportion to the depth of the beam. One of the most important limitations in most empirical formulas is either to neglect the size effect phenomena on shear capacity of concrete beams or not to take it into account properly. To compare the results of different equations for the size effect phenomenon, beams with depth greater than 600 mm were selected. There is a total of 19 beams available with depth greater than 600 mm in the complete data set used in this study. Since ACI and Zsutty's equation do not consider size effect, there is much scatter of data and R^2 values are negative for testing data. The scatter is shown in Figs. 10 and 11 for ACI equation, and in Figs. 12 and 13 for Zsutty's equation. It is also worth noticing that almost all the data points are overestimated by these two methods, and their use for such beams is rather unsafe.

Bazant and Sun equation and the ANN model developed in this study do con-

sider the size effect. The scatter of the data for the Bazant and Sun equation is given in Figs. 14 and 15; the ANN model prediction is given in Figs. 16 and 17. The training data consisting of 433 beams for the ANN model included 15 beams with depth greater than 600 mm. The testing data consisting of 189 beams had 4 beams with depth greater than 600 mm. It is evident that the ANN model almost perfectly correlated the size effect, and learnt the non-linearities inherent in the problem.

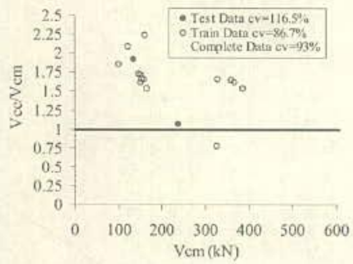

Fig. 10 *ACI equation prediction for $d > 600$ mm.*

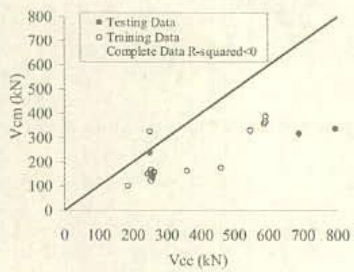

Fig. 11 *Scatter of Vcc by ACI equation for $d > 600$ mm.*

3.3 Deep beams

The shear failure mechanism of concrete beams changes with the a/d ratio, hence the ANN model was also checked separately for deep beams with a/d less than 2.5. There were 111 such beams in the complete data set, 79 of which fell into the training data set, and 32 were included in the testing data set. The ANN

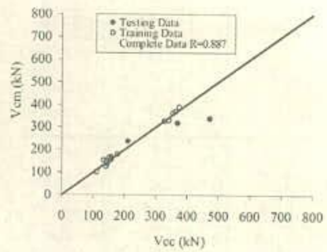

Fig. 15 *Scatter of Vcc by Bazant and Sun equation for* $d > 600$ *mm.*

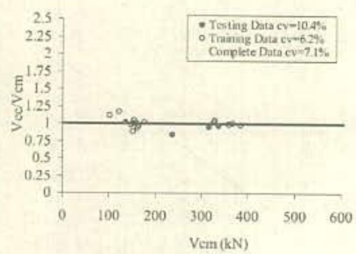

Fig. 16 *The ANN model prediction for* $d > 600$ *mm.*

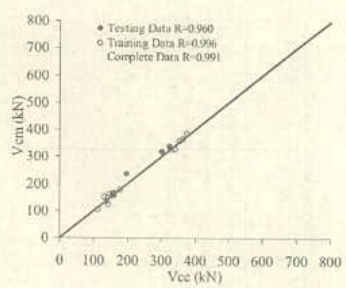

Fig. 17 *Scatter of Vcc by the ANN Model for* $d > 600$ *mm.*

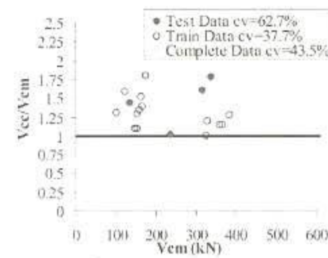

Fig. 12 *Zsutty's equation prediction for* $d > 600$ *mm.*

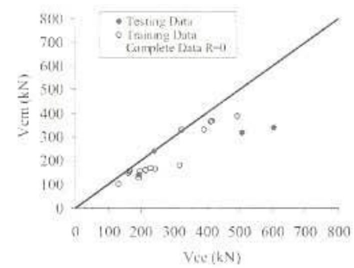

Fig. 13 *Scatter of Vcc by Zsutty's equation for* $d > 600$ *mm.*

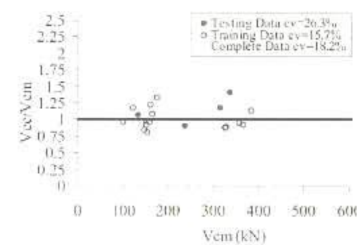

Fig. 14 *Bazant and Sun equation prediction for* $d > 600$ *mm.*

model turned out to be very robust and worked well both for slender as well as deep beams. The correlation coefficients for testing, training and complete data for deep beams are, respectively, 0.975, 0.99 and 0.987.

4. ANN Design Equation

In the preceding comparisons with tests, the formulas were made to represent the mean trend of the test data. The data points in Figs. 6 to 9 that fall above the 45° line are safe, whereas the data points falling below this line are on the unsafe side. The design formulas should, however, be introduced in such a manner that most of the test data are on the safe side of the predicted values. This is achieved by multiplying these formulas by a suitable factor (Appendix 2). For the ANN model this factor is I_f.

If $V_c \leq 150{,}000$ N, multiply V_c predicted by the ANN model by I_f equal to 0.65.

For $V_c > 150{,}000$ N, use $I_f = V_c^{0.23}/21$ but $0.65 \leq I_f \leq 0.9$.

The design plots of Vcm against Vcc for the ANN model, Bazant and Sun, ACI, and Zsutty's equations are shown, respectively, in Figs. 18, 19, 20 and 21. In these plots, the majority of data should lie above the inclined straight line, and this is well satisfied for the ANN design model (Fig. 10). However, for the existing ACI equation, the majority of points fall below the line, and on the other hand, many points lie high above the line, which represents an uneconomical design (Fig. 20).

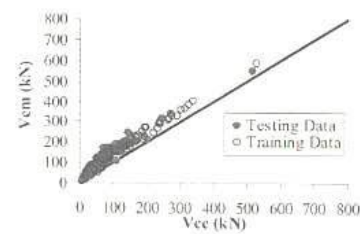

Fig. 18 *Design plot for the ANN model.*

5. Summary and Conclusion

The back-propagation approach was successfully applied in order to evaluate the shear load capacity of reinforced concrete beams with web reinforcement. The ANN model is composed of seven input nodes (neurons) for the seven input parameters, seven hidden nodes, and one output node for a single output of nominal shear load. In this research, we used the Levenberg–Marquardt back-propagation algorithm,

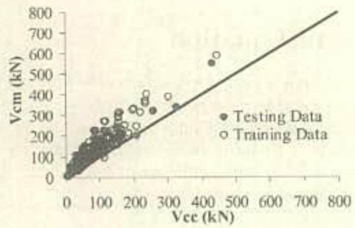

Fig. 19 *Design plot for Bazant and Sun equation.*

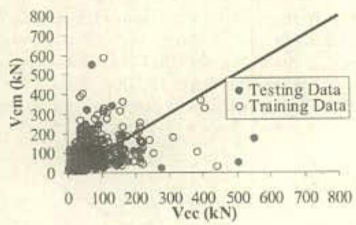

Fig. 20 *Design plot for ACI equation.*

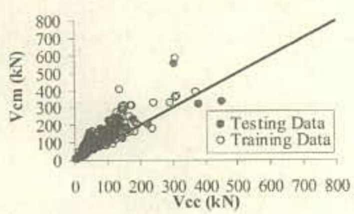

Fig. 21 *Design plot for Zsutty's equation.*

which is the fastest method for training moderate-sized feed-forward neural networks (up to several hundreds of weights). The ANN is trained on 433 beams data and then tested for its accuracy on 189 beams data, which are new to the ANN model. The prediction of the ANN model was compared with three methods, i.e. Bazant and Sun equation (1987), ACI code equation (2002), and Zsutty's equation (1971). The ANN model shows best results for the testing data and proved to be very robust. The ANN performed equally well both in case of slender and deep beams. In addition, the ANN also takes the "size effect" into account. A sample calculation is given in Appendix 1.

6. Appendix

6.1 Appedix 1: Calculation using the artificial neural network model

The use of ANN model to evaluate nominal shear load capacity of reinforced concrete beam with $\rho = 0.00663$, $a/d = 3.96$; $d = 390.6$ mm, $d_a = 19$ mm, $f'_c = 32.54$ N/mm^2, $b_w = 190.5$ mm, and $V_s = 16274.8$ N. The solution procedure with calculation is presented in Tab. V.

Hence, the ANN predicted V_c of 73772.6 N as compared to the actual V_c of 69460.4 N.

P, Input vector	Pn, normalized input vector (equation 1)	$N_1 = (W_1 Pn + B_1)$	$A_1 =$ log-sig(N_1)	$N_2 = W_2 x A_1 + B_2$	Normalized Network Output Tn=tan-sig(N_2)	T unnormalized output (equation 3)
0.00663	-0.8471	51.1476	1.0000	-1.0193	-0.7696	73772.6
3.96	-0.2251	-2.4062	0.0827			
390.6	-0.4262	1.0468	0.7402			
19	-0.0714	1.0703	0.7447			
32.54	-0.4470	8.5681	0.9998			
190.5	-0.5002	9.4718	0.9999			
16274.8	-0.7952	-4.6402	0.0096			

Tab. V *Procedure to calculate nominal shear load using the ANN model.*

6.2 Appendix 2

Bazant and Sun equation (1987)

$$V_c = 0.539\,\rho^{1/3}\left(\sqrt{f'_c} + 249.01\sqrt{\rho\left(\frac{a}{d}\right)^5}\right) \times \frac{1+\sqrt{\frac{5}{d_a}}}{\sqrt{1+\frac{d}{25 d_a\left(1+\frac{\rho_v}{\rho_o}\right)}}} b_w d \tag{7}$$

$$\frac{1}{\rho_o} = 400\left(1 + tanh\left(2\frac{a}{d} - 5.6\right)\right) \tag{8}$$

ρ_v is the percent stirrup steel ratio

For the design purpose, equation 7 is multiplied bythe factor of 0.69.

ACI code equation

$$V_c = 0.105\sqrt{f'_c}b_w d + 93.785\,\rho\frac{V_u d}{M_u}b_w d \le 0.291\sqrt{f'_c}b_w d \tag{9}$$

The ACI code equation 11.3.2 for the design is

$$V_c = 0.158\sqrt{f'_c}b_w d + 17.24\,\rho\frac{V_u d}{M_u}b_w d \le 0.291\sqrt{f'_c}b_w d \tag{10}$$

Zsutty's equation (1971)

$$V_c = 5.433\left[f'_c \rho\left(\frac{d}{a}\right)^4\right]^{1/3} b_w d \quad \text{for } \frac{a}{d} < 2.5 \tag{11}$$

$$V_c = 2.173\left[f'_c \rho\left(\frac{d}{a}\right)\right]^{1/3} b_w d \quad \text{for } \frac{a}{d} \ge 2.5 \tag{12}$$

The design equation is obtained by multiplying equation 11 and equation 12 by 0.75.

6.3 Appendix 3

$$W_1 = \begin{bmatrix} -44.8623 & -1.3211 & -14.1067 & 21.9775 & 0.8908 & 41.4911 & -6.2336 \\ 1.6424 & 1.6680 & -0.4511 & -.7847 & -.5764 & -2.1480 & 0.0278 \\ -0.7340 & -0.5881 & -0.7112 & 0.5431 & 1.8285 & -3.9063 & 0.7317 \\ -0.7680 & -0.6609 & -0.6724 & 0.5671 & 1.8040 & -3.8885 & 0.7623 \\ 0.6129 & 5.6380 & -0.4557 & -0.9247 & 0.0703 & 0.4542 & 1.5414 \\ 2.2042 & 6.7463 & 2.1208 & -2.3800 & -0.1296 & 1.3550 & 1.7754 \\ -0.6259 & 0.0443 & -1.2622 & -0.0803 & -0.1175 & -0.1425 & -0.8318 \end{bmatrix}$$

$$W_2 = \begin{bmatrix} -0.4734 & -2.2981 & 41.8479 & -42.2697 & -165.1080 & 66.5794 & -81.8363 \end{bmatrix}$$

$$B_1 = \begin{bmatrix} 24.5999 \\ -2.1978 \\ -0.5265 \\ -0.5077 \\ 11.5802 \\ 15.6229 \\ -6.4894 \end{bmatrix} \qquad B_2 = [99.4304]$$

[5] Dowla F. U., Rogers L. L.: Solving problems in environmental engineering and geosciences with artificial neural networks, MIT, Cambridge, Ma., 1995.

[6] Hadi N. S. M.; Neural networks applications in concrete structures" Computers and Structures, **81**, 2003, pp. 373-381.

[7] Hagan M. T., Demuth H. B., Beale M.: Neural network design, PWS, Boston, 1996.

[8] Mustafa Sarıdemir: Prediction of compressive strength of concretes containing metakaolin and silica fume by artificial neural networks, Advances in Engineering Software **40**, 5, May 2009, pp. 350-355.

[9] Mansour M. Y., Dicleli M., Lee J. Y., Zhang J.: Predicting the shear strength of reinforced concrete beams using artificial neural networks, Engineering Structures, **26**, 2004, pp. 781-799.

[10] More J. J.: The Levenberg-Marquardt algorithm: Implementation and theory, 1977.

[11] Watson G. A. (Ed.): Numerical Analysis, Springer, Heidelberg, pp. 105-116.

[12] Kumar S., Barai S. V.: Neural networks modeling of shear strength of SFRC corbels without stirrups, **10**, 2010, pp. 135-148 (available online).

[13] Wassim M. Ghannoum: Size effect on shear strength of reinforced concrete beams, 1998.

[14] Master Degree Thesis, Department of Civil Engineering and Applied Mechanics, McGill University, Montreal, Canada.

[15] Zsutty T. C.: Shear strength prediction for separate categories of simple beam tests, ACI Journal, Proceedings, **68**, 2, Feb. 1971, pp. 138-143.

7. Notations

The following symbols are used in this paper:

μ	=	longitudinal tensile steel ratio
a	=	shear span
ACI	=	American Concrete Institute
ANN	=	Artificial Neural Network
$\mathbf{B}_1$	=	bias vector for the hidden layer neurons
$\mathbf{B}_2$	=	bias vector for the output layer neuron
b_w	=	web width of beam
cv	=	coefficient of variation
d	=	distance from extreme compression fiber to centroid of tension reinforcement
d_a	=	maximum size of aggregate
f'_c	=	compressive strength of concrete
I_f	=	multiplying factor
maxP	=	vector containing maximum values of the original input
maxT	=	vector containing the maximum value of the target output
minP	=	vector containing minimum values of the original input
minT	=	vector containing the minimum value of the target output
P	=	matrix of the input vectors
Pn	=	matrix of normalized input vectors
Pn	=	matrix of normalized input vector
R	=	correlation coefficient
T	=	matrix of the output vectors
Tn	=	matrix of normalized target output vectors
Tn	=	matrix of normalized output vector
V_c	=	nominal shear load capacity at failure
Vcc	=	calculated concrete shear load capacity
Vcm	=	measured concrete shear load capacity
V_s	=	yield force in stirrups
$\mathbf{W}_1$	=	matrix of connection weights between the neurons of input and hidden layer
$\mathbf{W}_2$	=	matrix of connection weights between the neurons of hidden and output layer

References

[1] ACI Committee 318, Building Code Requirements for Structural Concrete (ACI 318 08) and Commentary (ACI 318R-08). American Concrete Institute, 2008, p. 147.

[2] Ahmad I., Javed M., Qaisar A.: Simplified equation for estimating the shear capacity of reinforced concrete beams without web reinforcement, Journal of Engineering and Applied Sciences, **19**, 2, July-Dec. 2000, pp. 61-68.

[3] Oreta A. W. C.: Simulating size effect on shear strength of RC beams without stirrups using neural networks, Engineering Structures, **26**, 2004, pp. 681-691.

[4] Bazant Z., Sun H.: Size effect in diagonal shear failure: influence of aggregate size and stirrups, ACI Material Journal, July-August, **84**, 4, 1987, pp. 259-272.