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Full Length Research Paper

A multilayer perceptron for predicting the ultimate shear strength of reinforced concrete beams

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A number of codes of practice exist that predict the maximum shear capacity of reinforced concrete beams. Since the behavior of reinforced concrete (RC) beams with non-homogeneous, non-isotropic, and nonlinear material under a combined shear and bending state of stress is very difficult to establish, these codes seem to under or over-estimate this shear capacity for many cases. This is attributed to the fact that the factors that affect the shear strength of RC beams are too many, making modeling of its actual behavior a hard task. In this paper, several multilayer perceptrons were constructed as an analytical alternative to existing expressions for predicting the shear capacity of RC beams. A large database of experimental tests of beams (574 samples) was utilized to train and test the networks. Both multilayer perceptrons' predictions and four different codes of practice for the shear capacity of RC beams were examined. It was found that, the predictions of multilayer perceptrons are superior to those of any of the current available code relationships.

Key words: Multilayer perceptron, neural networks, shear capacity, reinforced concrete (RC) beams, shear reinforcement.

INTRODUCTION

Structural engineers always attempt to improve the analysis, design, and control of the behavior of structural systems. Such behavior, however, is complex and often governed by both known and unknown multiple variables with their interrelationship generally unknown, nonlinear and sometimes very complicated. The traditional approach used in most research in modeling generally depends on performing a multi variable nonlinear regression analysis so that the major parameters are calibrated to fit the experimental results and to derive the relationships among the involved parameters.

By contrast, the use of multilayer preceptron technique, or alternatively called neural network (NN), provides an alternative method that may be more accurate in predicting the actual response. A neural network is a computational tool that attempts to simulate the architecture and internal operational features of the human brain and neurons systems. In a strict mathematical sense, neural networks do not provide closed form solutions for modeling problems but offer a complex and accurate solution based on a representative set of examples of the relationship.

Neural network modeling techniques have been widely applied in structural engineering fields in recent years. For example, it has been applied to the area of structural analysis, design, and modeling (Senouci, 2000; Zhao et al., 2001; Sirca and Adeli, 2001; Oreta and Kawashima, 2003; Yun et al., 2008); structural dynamic problems (Chang and Zhou, 2002; Taysi, 2010); structural performance evaluation (Pannirselvam et al., 2008, 2010; Noorzaei et al., 2008); damage detection of structures (Zang and Imregun, 2001; Tsai and Hsu, 2002; Seleemah et al., 2012); and in geotechnical engineering applications (Jan et al., 2002; Juang and Jiang, 2003; Juang et al., 2003). The common features of many of the successful applications of neural networks in prediction and modeling are that the quantities being modeled are governed by multivariate interrelationships and the data available are "noisy" or incomplete. Moreover, when neural network models are developed, there is no need to assume any functional relationship among the various variables unlike in regression analysis. Neural networks

Table 1. Ranges of parameters in database.

Parameter	Minimum	Maximum	Parameter	Minimum	Maximum
b_w *(mm)*	76.2	1000.0	ρ_l *(%)*	0.14	6.64
d (mm)	110.0	2000.0	f_{yl} *(MPa)*	275.86	1779.31
a/d	1.56	8.03	ρ_v %	0.00	1.47
$f_c^{'}$ *(MPa)*	11.97	105.36	f_{yv} *(MPa)*	250	1431

automatically construct the relationships and adapt based on the data used for training.

A number of codes of practice exist that gives equations to predict the shear behavior of RC beams both with and without shear reinforcement. While these major codes are very important, there prediction seems to under or over-estimate this shear capacity in many cases. This is due to the fact that the behavior of RC beams with nonlinear, non isotropic and nonhomogeneous material under combined shear forces and bending moments is very complicated. Moreover, the shear strength of RC beams is affected by too many factors. This adds to the complexity of modeling its shear behavior.

While many efforts have been conducted to understand the shear behavior of reinforced concrete beams and/or to drive equations for estimating such shear capacity, some researchers explored the application of neural networks for such predictions. For example, Sanad and Saka (2001) applied the neural networks to predict the ultimate shear capacity of reinforced concrete deep beams; Mansour et al. (2004) successfully used the neural networks for prediction of the shear capacity of reinforced concrete beams with shear reinforcement; Oreta (2004) applied neural networks on a set of 155 experimental tests to simulate the size effect on the shear strength of reinforced concrete beams without shear reinforcement. Seleemah (2005) compared the predictions of neural networks with eight different equations for predicting the shear capacity of beams without shear reinforcement.

Rao and Babu (2007) constructed a hybrid neural network model which combines the features of feed forward neural networks and genetic algorithms for the design of beam subjected to moment and shear. Yang et al. (2007) built optimum multi-layered feed-forward neural network models using a resilient back-propagation algorithm to predict the shear capacity of reinforced concrete deep and slender beams. Dopico et al. (2008) applied the neural network technique to predict the shear strength of high and normal strength reinforced concrete beams with or without shear reinforcement. Kumar and Yadav (2008) applied a three-layer feed forward neural network with back propagation algorithm on 194 test results of reinforced concrete rectangular beams with web reinforcement failing in shear.

The intended aims of this study are: (i) to explore the feasibility of using neural networks in predicting the ultimate shear capacity of RC beams having a wide range of different variables including the existence or absence of shear reinforcement; (ii) to compare the results of neural network predictions with both the experimental values and those obtained using four major codes of practice, namely the ACI 318M-08, EC2, NZS 3101, and CSA codes; and (iii) to highlight the specific reasons that leads to over or under-estimation of the beams' shear capacity by these codes.

For this, a large database of 574 specimens that include normal and high-strength concrete beams with different percentages of longitudinal and shear reinforcement was retrieved from existing literature. The shear capacity of these beams was calculated utilizing both the afro mentioned codes and several neural networks having different architectures. Finally a comparison of the predictions obtained by the most successful network and those of the four codes of practice is presented.

METHODOLOGY

A databank of beams that satisfy agreed upon criteria was established and called the evaluation shear databank, Reineck et al. (2003). This databank contained 439 shear tests collected from 64 references. All beams in this database have a rectangular cross section, do not contain shear reinforcement, and were subjected to point loads. Extensive discussions and review on this databank was then conducted by the ACI subcommittee 445-F “Beam Shear” which led to extraction of a revised version (398 tests) that was intended to serve as a basis for any code changes. This database was combined with the database reported by Mansour et al. (2004) that contains a total of 176 test samples of beams with shear reinforcement collected from 15 references to have a total of 574 samples containing beams with or without shear reinforcement. This database was utilized in this study to evaluate and demonstrate the capability of the multilayer perceptron technique for predicting the shear capacity of reinforced concrete beams. Moreover, it was also used for evaluating four different codes of practice that exist for predicting such shear capacity.

It should be pointed out that the aforementioned database covers a very wide range of beam depths, breadths, shear span to depth ratios, maximum aggregate size used in concrete and its tensile and compressive strengths, main reinforcement percentage, shear reinforcement percentage, and yield stresses of longitudinal and shear reinforcement. Table 1 summarizes the ranges of the parameters covered by this database.

Shear strength of RC beams using building codes

Four major codes for estimation of the shear capacity of reinforced concrete beams were examined. These are ACI 318M-08, EC2, NZS 3101, and CSA. The expressions utilized by each of these codes are presented as follows:

ACI 318M-08(2008)

The shear provisions of the ACI building code states that the nominal shear strength V_n of a reinforced concrete beam can be computed as:

$$V_n = V_c + V_s \tag{1}$$

where V_c is nominal shear strength provided by concrete, and V_s is nominal shear strength provided by shear reinforcement. The concrete contribution to the shear strength can be calculated for members subject to shear and flexure only, from the following relationship:

$$V_c = 0.17\lambda\sqrt{f_c^{'}}.b_w d \tag{2}$$

Where λ equals 1.0 for normal weight concrete, b_w and d are the beam width and depth, respectively; and $f_c^{'}$ is the concrete cylinder compressive strength. The steel contribution can be calculated as:

$$V_s = \frac{A_v f_{yv} d}{s} \tag{3}$$

where A_v is the area of shear reinforcement within spacing s; and f_{yv} is the tensile yield stress of the shear reinforcement perpendicular to axis of the member and shall not exceed 420 MPa.

EC2 (2004)

This code gives the following relationship for beams without web reinforcement

$$V_n = V_c = \left[0.18k(100\rho_l f_c^{'})^{\frac{1}{3}}\right]b_w d \geq 0.035k^{1.5}\sqrt{f_c^{'}}b_w d \tag{4}$$

Where $k = 1+\sqrt{\frac{200}{d}} \leq 2.0$ (d in mm) and $\rho_l \leq 0.02$

For the case of beams with web reinforcement

$$V_n = Max\left[V_c, (\rho_v f_{yv}\cot\theta)b_w d\right] \leq v_e \frac{f_c^{'}}{1.5}/(\cot\theta + \tan\theta) \tag{5}$$

Where $v_e = 0.6(1 - f_c^{'}/250)$ and $1 \leq \cot\theta \leq 2.5$

Where ρ_l and ρ_v are the longitudinal and shear steel reinforcement ratios, respectively; and θ is the angle of web reinforcement to longitudinal axis of beam.

NZS 3101(1995)

This code is applicable for members with concrete strength up to 100 MPa. The concrete contribution to the shear capacity is expressed as:

$$V_n = [(0.07 + 10\rho_l)\sqrt{f_c^{'}}].b_w d \tag{6}$$

The concrete stress term should be within the minimum and maximum limits of $0.08\sqrt{f_c^{'}}$ and $0.2\sqrt{f_c^{'}}$, respectively. The shear reinforcement contribution is similar to that of the ACI code given by Equation (3).

CSA (Canadian Standard Association) building code(1994)

The simplified method of this code considers the shear reinforcement contribution as that of the ACI code given by Equation (3) and the concrete shear contribution, V_c, is given as dependent on the shear reinforcement and the effective depth of the beam, d, as following

$$V_c = 0.2\sqrt{f_c^{'}}.b_w d \tag{7}$$

$A_v \geq 0.06\sqrt{f_c^{'}}b_w s / f_{yv}$ or
$d \leq 300mm$

$$V_c = \left(\frac{260}{1000+d}\right)\sqrt{f_c^{'}}.b_w d \geq 0.1\sqrt{f_c^{'}}.b_w d \tag{8}$$

$A_v < 0.06\sqrt{f_c^{'}}b_w s / f_{yv}$ and
$d > 300mm$

Multilayer perceptron architecture

A multilayer perceptron is a nonlinear dynamic system consisting of a large number of highly interconnected processing units, called artificial neurons. The main computational characteristics of multi-layer perceptrons are their ability to learn functional relationships from examples and to discover patterns and regularities in data through self-organization. So, they are very suitable for modeling the nonlinear mapping type of problems.

A multilayer perceptron consists of a collection of simple processing units or nodes connected through links called connections. The topology or architecture of a multilayer perceptron is presented schematically in Figure 1, In which, a four-layered feed-forward multilayer perceptron is represented in the form of

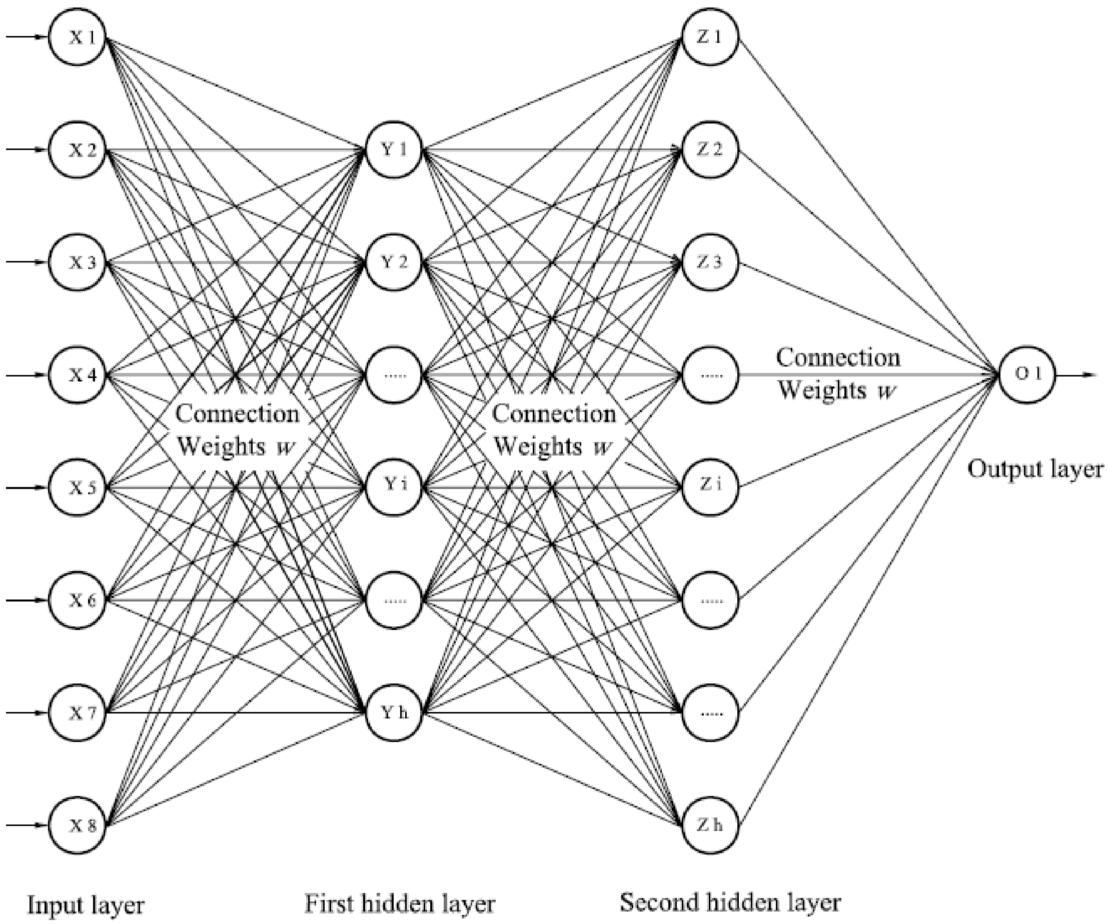


Figure 1. Typical architecture of a multilayer perceptron.

a directed graph, where the nodes represent the processing unit, the arrows represent the connections, and the arrowheads indicate the normal direction of signal flow.

The processing units may be grouped into layers of input, hidden, and output processing units. The main tasks of processing units are to receive input from its neighboring units which provide incoming activations, compute an output, and send that output to its neighbors receiving its output. The strength of the connections among the processing units is provided by a set of weights (w_i) which affect the magnitude of the input that will be received by the neighboring units. The output produced by the output processing units is compared to the target output data, and the weights are appropriately modified or adjusted based on training or learning rule. Eventually, if the problem can be learned, a stable set of weights adaptively evolves that will produce good results.

The connections between the neurons are individually weighed so that the total of i inputs (X_i) to the single neuron is:

$$\text{Input}=\sum_i w_i X_i \tag{9}$$

The weights may be positive or negative such that some inputs will be excitatory and others will be inhibitory. This input passes through an activation function to produce the values of Y_i or Z_i of the hidden layer(s) or O_i of the output layer. The activation function may have many forms. The most used and effective form in our case is the sigmoid function defined as:

$$\text{Output}=1/\left[1+e^{-\alpha(Input)}\right] \tag{10}$$

where α is a constant that typically varies between 0.01 and 1.0.

Signals are received at the input layer, pass through the hidden layers, and reach the output layer, producing the output of the network. The learning process primarily involves the determination of connection weight matrix and the pattern of connections. It is through the presentation of examples, or training cases, and application of the learning rule that the network obtains the relationship embedded in the data.

Input and output layers of neural networks

In this study, the neural networks were designed to have an input layer that consists of eight input nodes representing the most important parameters that affect the shear capacity of reinforced concrete beams. Based on careful study of recent approaches for the shear phenomena in concrete members (refer to ASCE-ACI shear and torsion committee 445, 1998; Reineck et al., 2003) , it was decided to design the input layer to consist of 1- beam depth (d); 2- beam breadth (b_w); 3-shear span to depth ratio (a/d); 4- concrete cylinder compressive strength $f_c^{'}$; 5- percentage of Main longitudinal reinforcement (ρ_l); 6- longitudinal steel yield stress(f_{yl}); 7- percentage of shear reinforcement (ρ_v); and 8- shear reinforcement yield stress (f_{yv}). The output layer consisted of one node representing the ultimate shear capacity of the beam.

Training of the network

In a multilayer feed forward neural networks, *training* refers to the iterative process involving the presentation of training data to the network, the invocation of learning rules to modify the connection weights, and, usually, the evolution of the network architecture, such that the knowledge embedded in the training data is appropriately captured by the weight structure of the network. During the training phase, the training data consists of input and associated output pairs representing the problem that the network should learn.

Training data and test data

An important factor that can significantly influence a network's ability to learn and generalize is the number of patterns in the training set. Increasing the number of training patterns, though increases the time required to train a network, provides more information about the shape of the solution surface, and thus increases the potential level of accuracy that can be achieved by the network. Since a total of 574 data patterns were available in this study, it was decided to use 50% of the data for the training process (287 beams) and save the other 50% for testing or validation. Training data were checked to make sure that they satisfy a good distribution over the problem domain.

Back propagation network learning algorithm

The training phase of the network is implemented by using a learning algorithm such as the popular and effective back propagation algorithm. The training phase of the algorithm consists of two passes. The forward pass computes the network output for a given set of connection weights and input data. The backward pass computes the error of the network with respect to the target outputs and this error is passed backward to the network and is used to modify the connection weights. Usually, an error criterion for the network output is chosen and the maximum number of cycles is set to provide a condition for terminating the simulations. The performance of the neural networks can be monitored by observing the convergence behavior of the error with respect to the number of cycles. If the network "learns," the error will approach a minimum value. After the training phase, the neural networks can be tested for other input data where the final values of the weights obtained in the training phase are used. No weight modification is involved in the testing phase.

Network data preparation

Neural networks are very sensitive to absolute magnitudes. To minimize the influence of absolute scale and numerical overflow, all inputs and outputs to neural networks were scaled so that they correspond roughly to the same range of values. Because of the property of the sigmoid function which is asymptotic to values 0 and 1, the derivative at or close to values 0 and 1 will approach zero producing very small signal error which results in slow learning. To avoid the slow rate of learning near the end points specifically of the output range, the data were scaled between the interval 0.1 and 0.9.

Network validation and error analysis

A neural network model, after it has been trained by presenting it with a set of training patterns, has to be empirically validated. The usual practice for neural network model validation is to evaluate the network performance measure using a selected error metric based on data (referred to as test data) that was not used in the training phase. Aside from validating the trained network, this performance measure is often used in research to show the superiority of certain network architecture. The evaluation and validation of neural network prediction model can be done by using common error metrics such as the root mean squared error (RMS). The definitions for RMS error is given by,

$$RMS = \sqrt{\sum_{i=1}^{n}\sum_{j=1}^{m}(O_{ij} - Y_{ij})^2 / nm} \tag{11}$$

Where n is the number of patterns in the validation set; m is the number of components in the output vector; O is the output of a single neuron; and Y is the target output for the single neuron.

Network topology

Since there is no direct and precise way of determining the most appropriate number of hidden layers and optimum number of neurons to include in each hidden layer for a specific problem, a trial and error procedure is typically used to approach the best network topology for a particular problem. In this paper, several network topologies were examined. These included networks with one hidden layer containing from one to seventeen neurons in the single hidden layer (a total of seventeen networks); and networks with two hidden layers containing from two to eight neurons in the first hidden layer; and from two to ten neurons in the second hidden layer (a total of twenty networks). The target network would be the one that produces minimum error for both the training and testing patterns based on statistical evaluation.

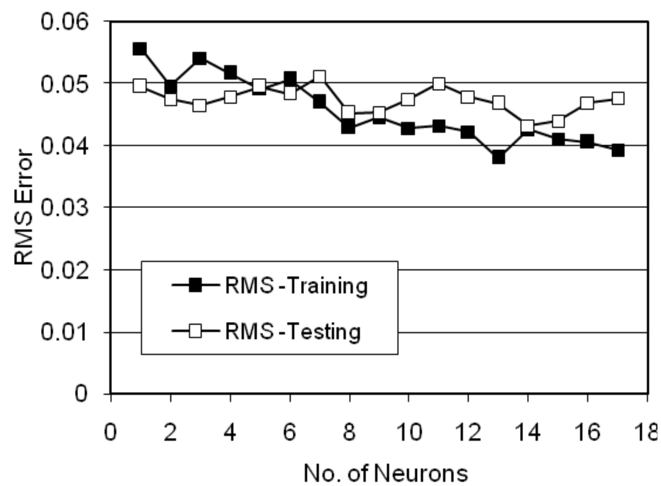
RESULTS AND DISCUSSION

Achieving best network

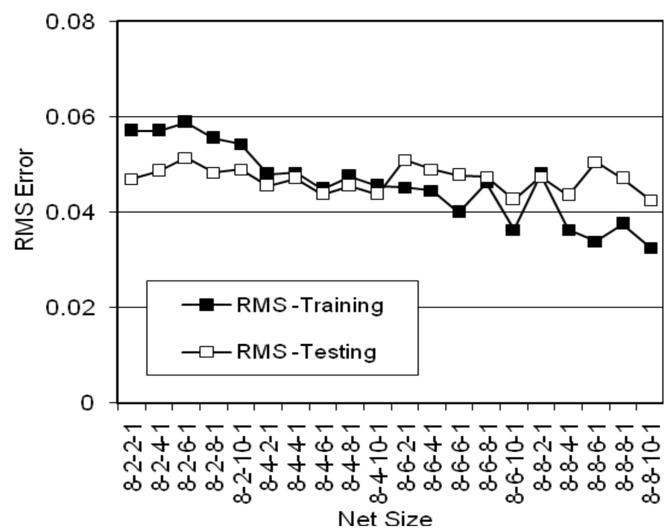
The performance of different networks in terms of RMS error of both training and testing patterns is shown in Figure 2. Clearly, increasing the number of neurons causes the RMS training error to decrease.

Six of the best networks that perform well during training and testing phases were selected and highered for an extra evaluation. These networks are NN 8-2-1, NN 8-5-1, and NN 8-14-1 which have one hidden layer containing 2, 5, and 14 neurons, respectively; and NN 8-4-2-1, NN 8-6-10-1, and NN 8-8-10-1 which have two hidden layers containing 4 and 2, 6 and 10, and 8 and 10 neurons in the first and second hidden layers, respectively. It is worth mentioning that networks NN 8-2-1, NN 8-5-1, and NN 8-4-2-1 were selected to represent small-sized networks that perform relatively well during both training and testing phases.

To judge which network performs better, the ratios of experimental to model predicted shear capacity



(a) Single Hidden Layer Networks



(b) Two Hidden Layers Networks

Figure 2. RMS error for different networks.

$\gamma_{mod}=V_{exp}/V_{pred}$ were calculated for all patterns, that is 574 pattern sets. The results are shown in Figure 3, which shows the maximum, minimum, average, standard deviation (SD), and the coefficient of variance (COV), for each of the tested networks. Moreover, a comparison of the experimental versus predicted shear capacity by the aforementioned six networks for all 574 data patterns is shown in Figure 4. The line of equality and the lines of plus or minus 10% error are also plotted on the figures to facilitate the visualization and judgment on the results. The network which gives results closer to the equality line is of course better. Using judgment on both figures, it was decided to select NN 8-8-10-1 as the most successful network. The histogram of ratio between experimental and predicted shear capacity for this network is shown in Figure 5. The histogram looks very close to the bell shape and it is nearly symmetrical with its maximum occurring at γ_{mod} = 1.0. However, very few odd results appeared at γ_{mod} = 1.80 (3 cases) and γ_{mod} = 2.20 (2 cases).

Comparison with different models

The prediction of the shear capacity of all 574 beam specimens were calculated using NN 8-8-10-1, together

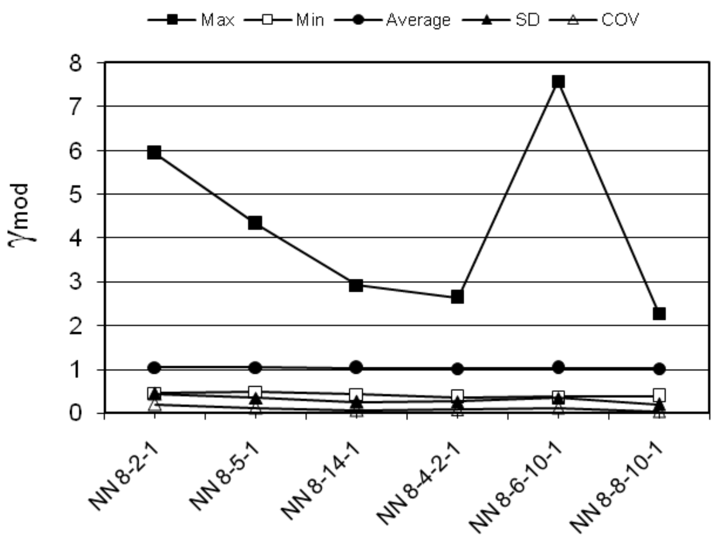


Figure 3. Statistical data for the ratio between experimental and predicted shear capacity for different networks

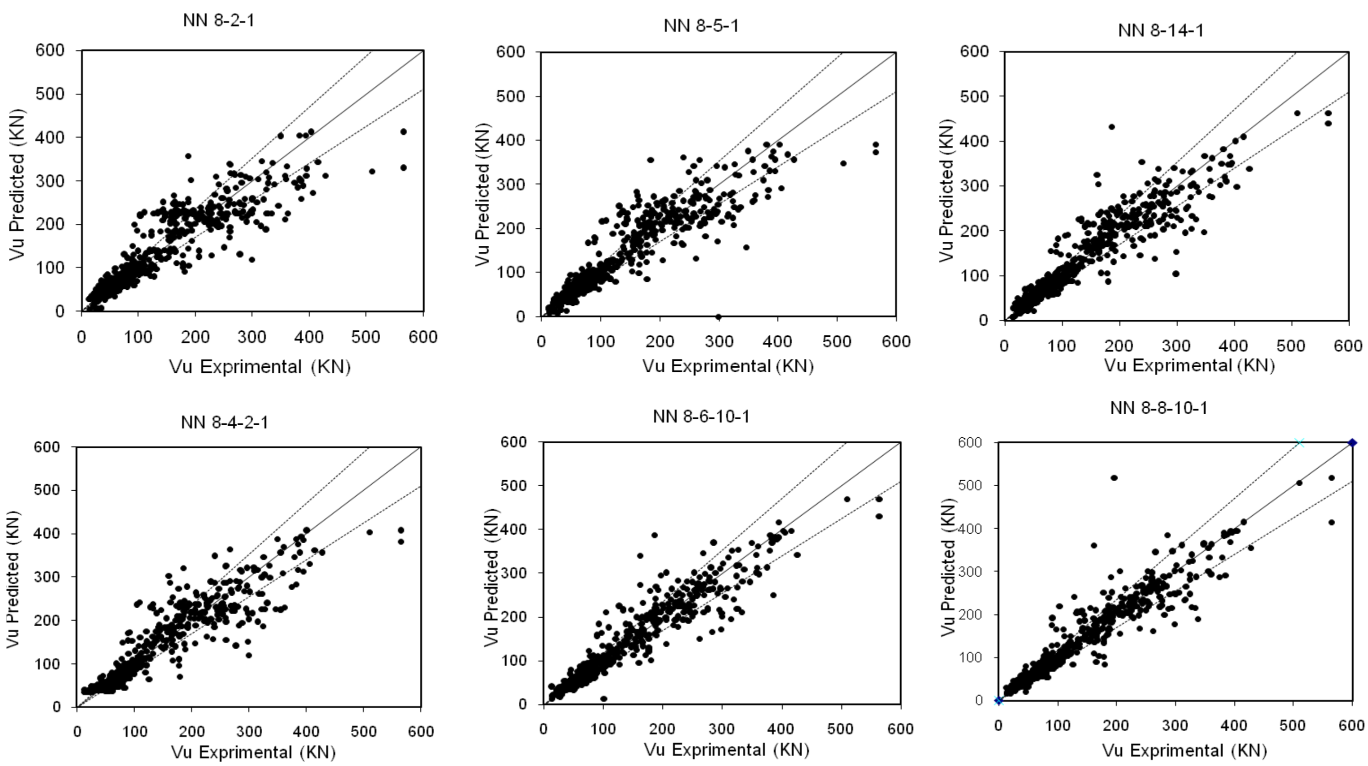


Figure 4. Comparison of experimental and predicted shear capacity for different networks.

with the four different codes mentioned earlier. The obtained results are shown in Figure 6, which shows, on separate plots, comparisons between experimental versus predicted shear capacity. It is clear from Figure 6 that the different codes give wide variations on either sides of the equality line. This means that these codes underestimate the shear capacity for some specimens and overestimate the shear capacity for other specimens. On contrast, the predictions of the neural network are much better with most results laying on or very close to

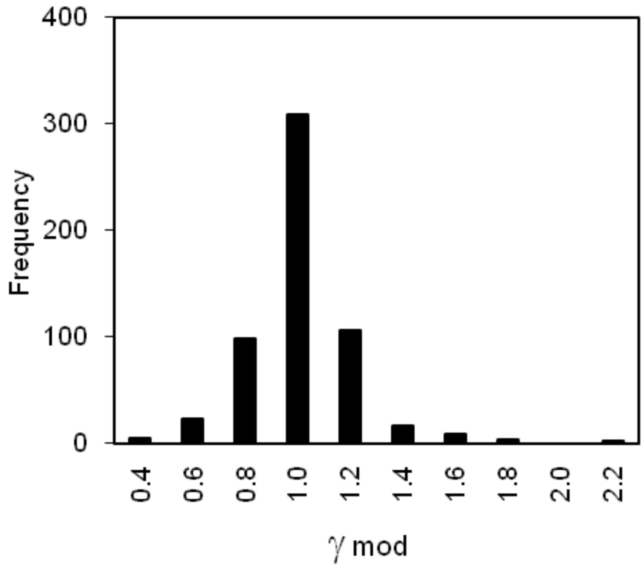


Figure 5. Histogram of ratio between experimental and predicted shear capacity for NN 8-8-10-1.

the equality line. This accuracy suggests that the most critical variables that control the shear capacity of concrete beams are the variables that have been used as input data to the neural network model. It also suggests that, in special circumstances such as rehabilitation of existing structures, where prediction of the accurate shear capacity of building beams or bridge girders are crucial, using a software that incorporates the neural network technique might be recommended.

The ratio of the experimental to the predicted shear capacity by specific code $\gamma_{mod}=V_{exp}/V_{pred}$ can be interpreted as the additional factor of safety implied by this code since no strength reduction factor was applied during calculations of any code's shear capacity prediction. For economy considerations, this additional safety factor should not be very large since there is a concrete strength reduction factor, γ_m, that is applied during any design process. The ratio γ_{mod} also should not be too less than unity since this means that the method overestimate the shear capacity of the beam which may lead to unsafe design.

A comparison of statistical calculations on the ratio of the experimental to the predicted shear capacity for all models and for all data patterns was conducted and the results are shown in Figure 7. Clearly, the neural network method gives best results with maximum ratio of 2.27, minimum of 0.38, and an average of 1.01. All codes have maximum ratio laying between 5.2 and 6.4, minimum between 0.15 and 0.19, with an average between 1.25 and 1.52. Both the SD and SV are minimum for the neural network method.

To describe the influence of dominant parameters on prediction of each model, the ratio of actual to predicted shear capacity is plotted versus the primary parameters in Figures 8 to 12. A common feature of all the plots is the very large scatter in the predictions by different codes in which γ_{mod} ranged between 0.15 to 6.4.

Figure 8 shows the plot of γ_{mod} with the shear span to depth ratio (*a/d)*. Most of the experimental tests were conducted for *a/d* ratio less or equal to 4.0. A large scatter is noticed in the predictions made by all codes for *a/d* ratios laying between 2.0 and 4.0. For all codes, the additional safety factor, γ_{mod}, increase with the decreases in a/d ratio indicating a beneficial influence due to direct load transfer that is not captured by these codes. Results obtained from the neural network indicate consistent accuracy in all ranges of *a/d* indicating a well capture of the shear phenomena.

The variation of the additional safety factor, γ_{mod}, with the concrete compressive strength for the models considered in this study is shown in Figure 9. Most of the testes in the database were carried out for normal strength concrete (NSC) having compressive strength less than 45.0 MPa. The scatter of the predictions by different codes for NSC specimens is very apparent. For concrete strength more than 45.0 MPA, the ACI, NZS, and CSA codes are generally conservative. The EC2 seems to overestimate the shear capacity for many specimens. Among all the shown models, the results obtained from the neural network is the most consistent one, having values close to unity for a wide variation of the concrete compressive strengths.

The variation of the additional safety factor, γ_{mod}, with beam depth, *d,* is shown in Figure 10. The majority of specimens had depth less than 500 mm. All codes yield large scatter of the results for specimens with depths in the range (d = 200 to 400 mm). The additional safety factor, γ_{mod}, predicted using different codes decreases with depth indicating improper capturing of the effect of depth on the overall shear capacity of beams. In contradiction to all codes, the predictions of the neural network model are more consistent and closer to unity.

Figure 11 shows the plot of γ_{mod} with the longitudinal reinforcement tensile strength indicator ($f_{yl} .\rho_l$). Results obtained using different codes show a general increase in the model's additional safety factor, γ_{mod}, with the increase in ($f_{yl} .\rho_l$) indicating a pronounced beneficial effect of the longitudinal reinforcement tensile strength that is not properly captured by any of these codes. While the yield strength of the longitudinal reinforcement is not included in any of the selected codes, the longitudinal reinforcement ratio, (ρ_l), is included only in the EC2 and the NZS codes but it seems that the beneficial effect of reinforcement exceeds what is included in their relationships. The performance of the neural network model is superior to all other models. It is not only unaffected by the change in the longitudinal reinforcement tensile strength, but also gives values of γ_{mod} very close to unity.

Lastly, Figure 12 shows the plot of γ_{mod} with the shear reinforcement tensile strength indicator ($f_{yv} .\rho_v$). Results

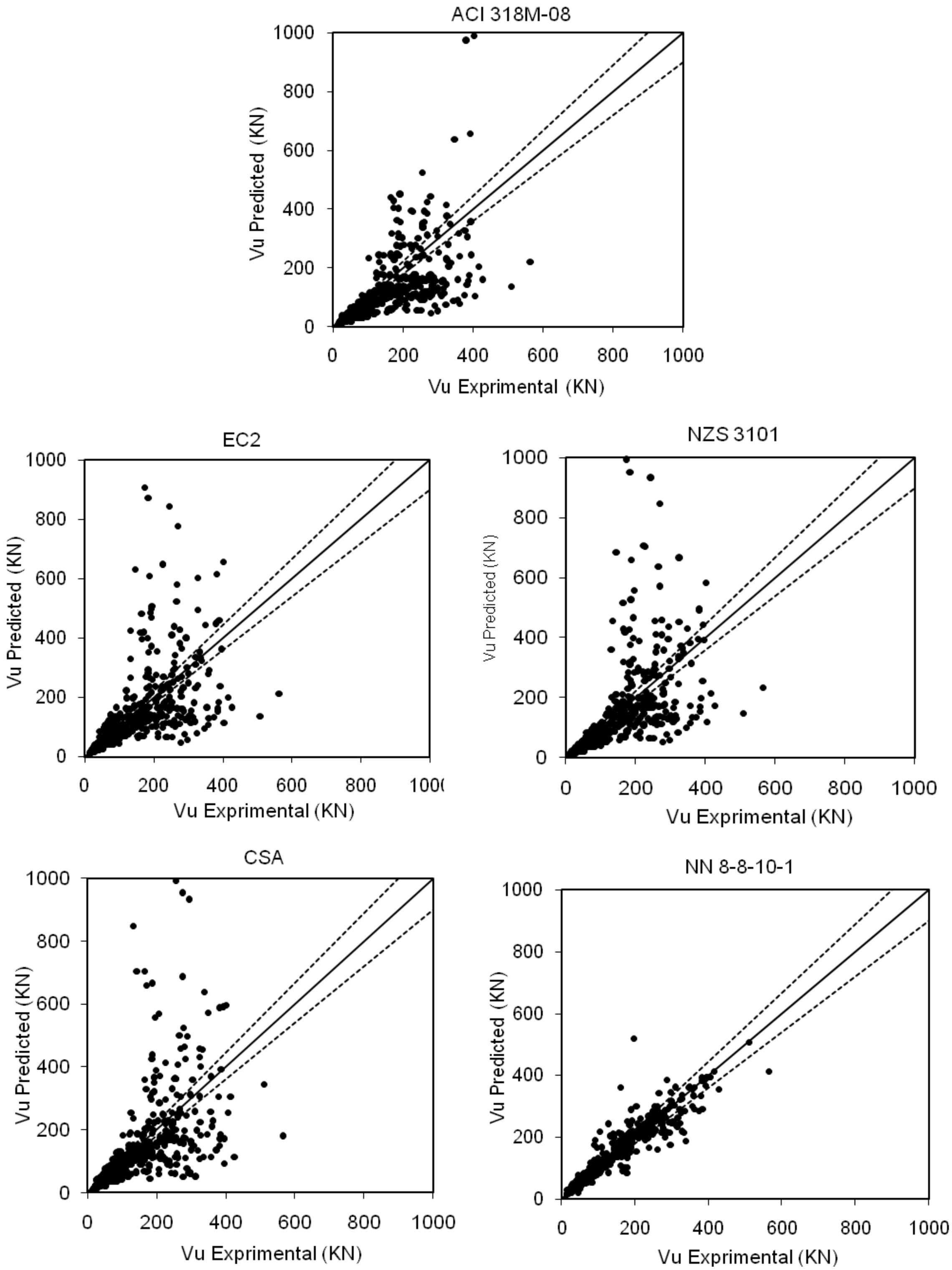


Figure 6. Comparison of experimental and predicted shear capacity for 573 specimens.

obtained using different codes show a serious decrease in the model's additional safety factor, γ_{mod}, with the increase in ($f_{yv}.\rho_v$) indicating an overestimation of the effect of the shear reinforcement effect. This overestimation is less pronounced in the CSA. This is due to the fact that this specific code puts limitation on the concrete shear contribution based on the shear reinforcement ratio. Once again, the performance of the

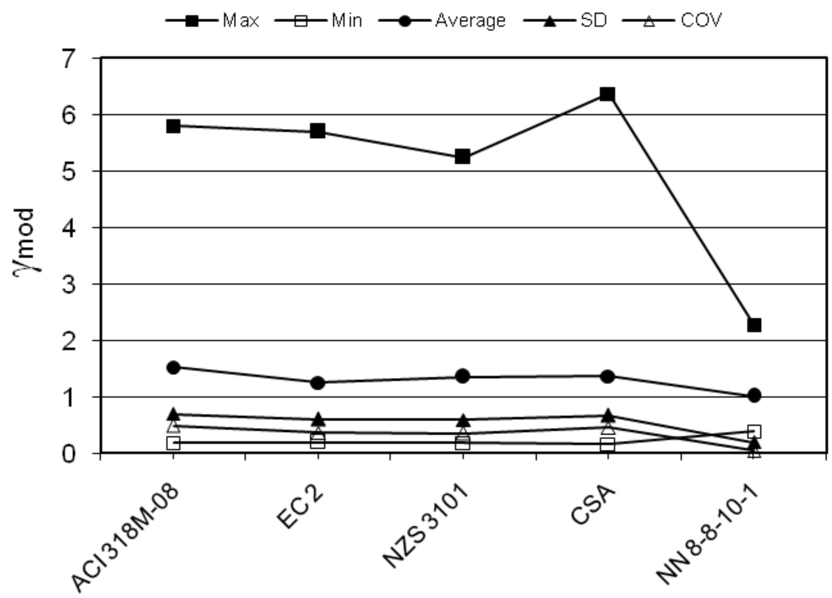


Figure 7. Statistical data for the ratio between experimental and predicted shear capacity for different shear proposals.

neural network model is superior to all other models indicating a good capability to give reasonable solution for such complicated phenomena.

Summary and conclusions

Different relationships have been proposed by existing codes of practice for predicting the shear capacity of concrete members. Unfortunately, the relationships differ considerably in their selected parameters since there is no generally accepted model for the load transfer and the ultimate shear capacity of reinforced concrete beams.

A Large database of experimental work conducted on beams with and without shear reinforcement was collected. This database contained a total of 574 tests. The database covered a very wide range of beam parameters including their dimensions, concrete strengths, reinforcement ratios and yield stresses, and shear span to depth ratios.

This database was utilized in this study to evaluate four different existing codes of practice for predicting the shear capacity of beams. These codes are ACI 318M-08, EC2, NZS 3101, and CSA. Moreover, the database was used to evaluate and demonstrate the capability of the feed-forward back propagation neural networks for predicting such shear capacity.

Based on careful study of recent approaches for the shear phenomena in concrete members, it was decided to design the neural network to have eight nodes in the input layer containing data regarding the beam depth (d), breadth (b_w), shear span to depth ratio (a/d), concrete cylinder compressive strength $f_c^{'}$, percentage of main reinforcement (ρ_l), longitudinal steel yield stress (f_{yl}), percentage of shear reinforcement (ρ_v), and shear steel yield stress (f_{yv}). The output layer consisted of one node representing the ultimate shear capacity of the beam.

Several network topologies were examined. These included seventeen networks with one hidden layer and twenty networks with two hidden layers containing from 2 to 10 neurons in each hidden layer. All these networks were trained on 287 shear tests and performance of these networks on both 287 training and 287 testing data sets was compared and the one with the best prediction was selected as the successful one.

The predictions of the neural network and those of the different codes were compared. It was found that, among all the existing models, the results obtained from the neural network are the most accurate results, giving values of maximum shear capacity very close to the experimental values. Moreover, the results obtained using the neural network were very consistent and covered a very wide range of variation of any of the input parameters.

This accuracy suggests that the most critical variables that control the shear capacity of concrete beams are the eight that have been used as input data to the neural network model. It also suggests that, in special structures, where prediction of the accurate shear capacity of building beams or bridge girders are crucial, using a software that incorporates the neural network technique might be recommended.

It was observed that for small *a/d* ratios there is a beneficial influence on the shear capacity due to direct load transfer. Moreover, there is a pronounced beneficial effect of the longitudinal reinforcement tensile strength on

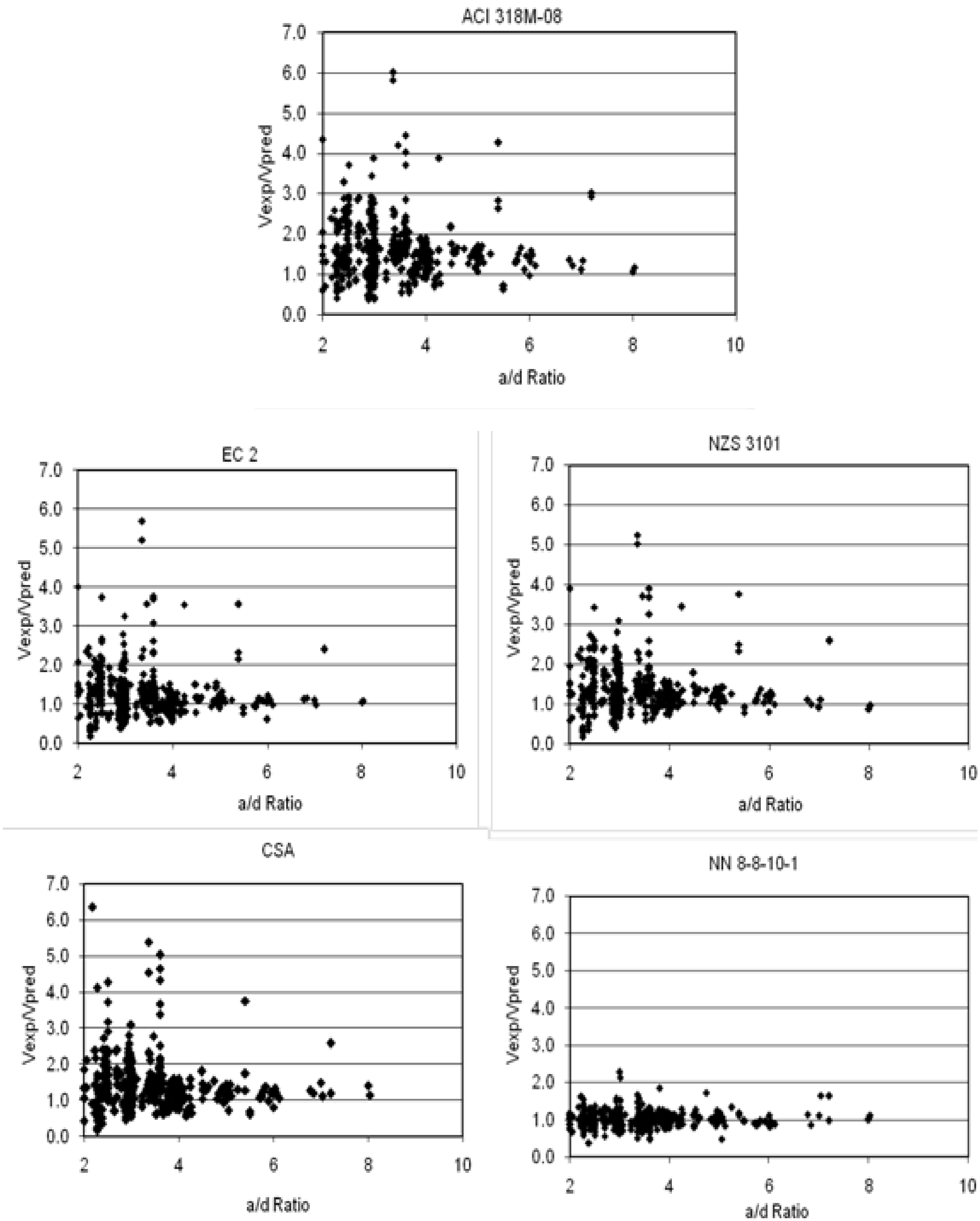


Figure 8. Experimental to predicted shear capacity versus a/d ratio for different shear proposals.

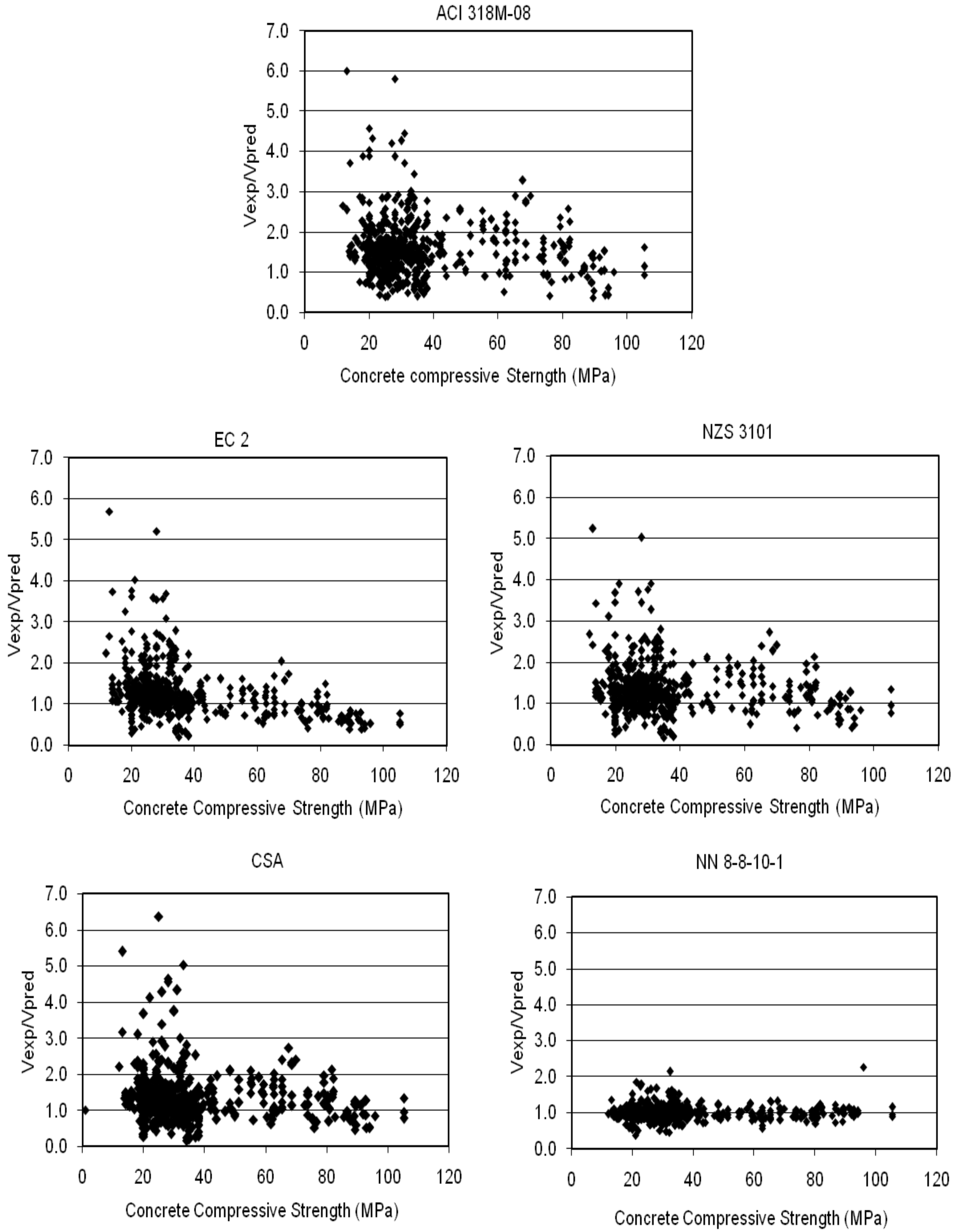


Figure 9. Experimental to predicted shear capacity versus concrete compressive strength for different shear proposals.

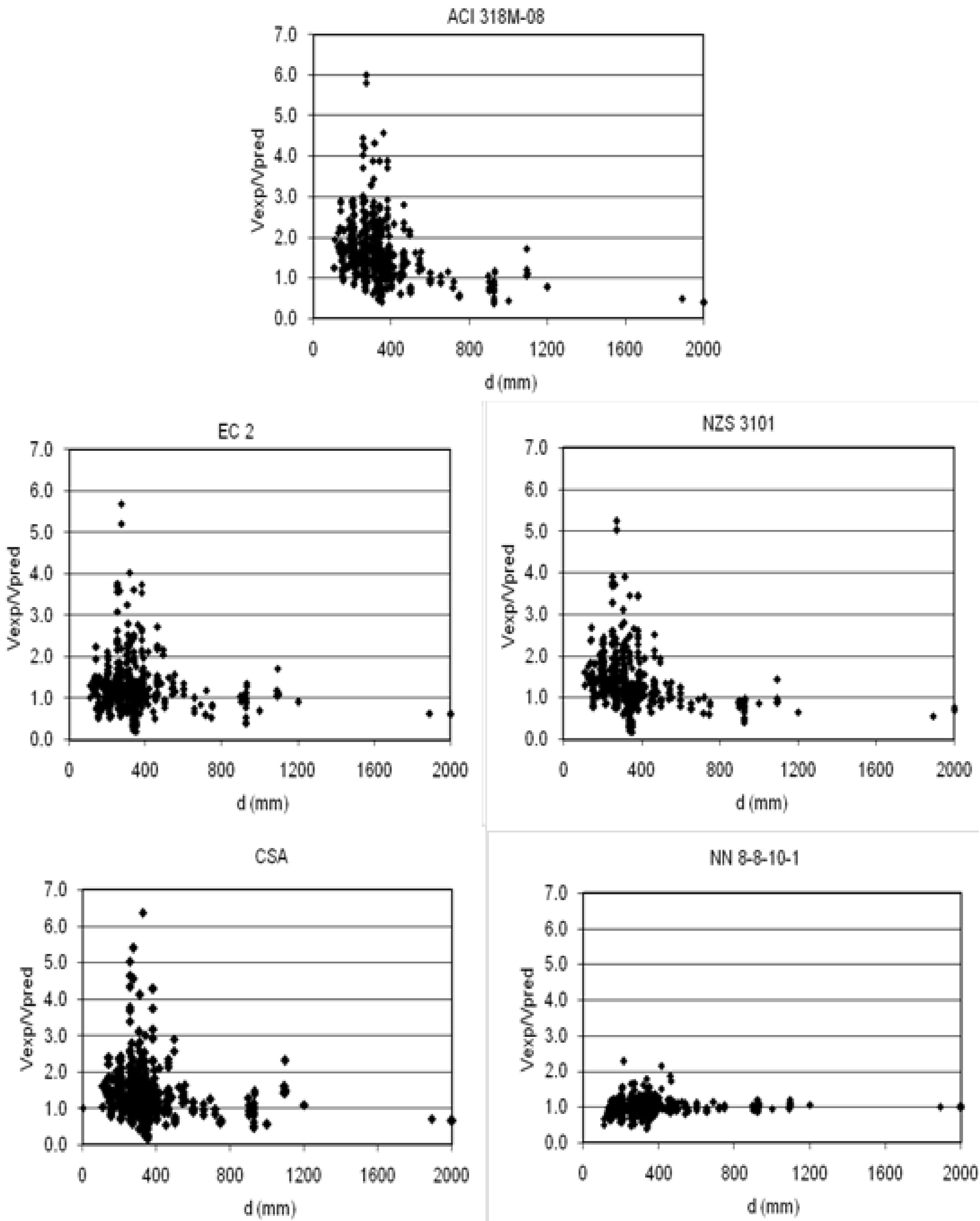


Figure 10. Experimental to predicted shear capacity versus beam depth for different shear proposals.

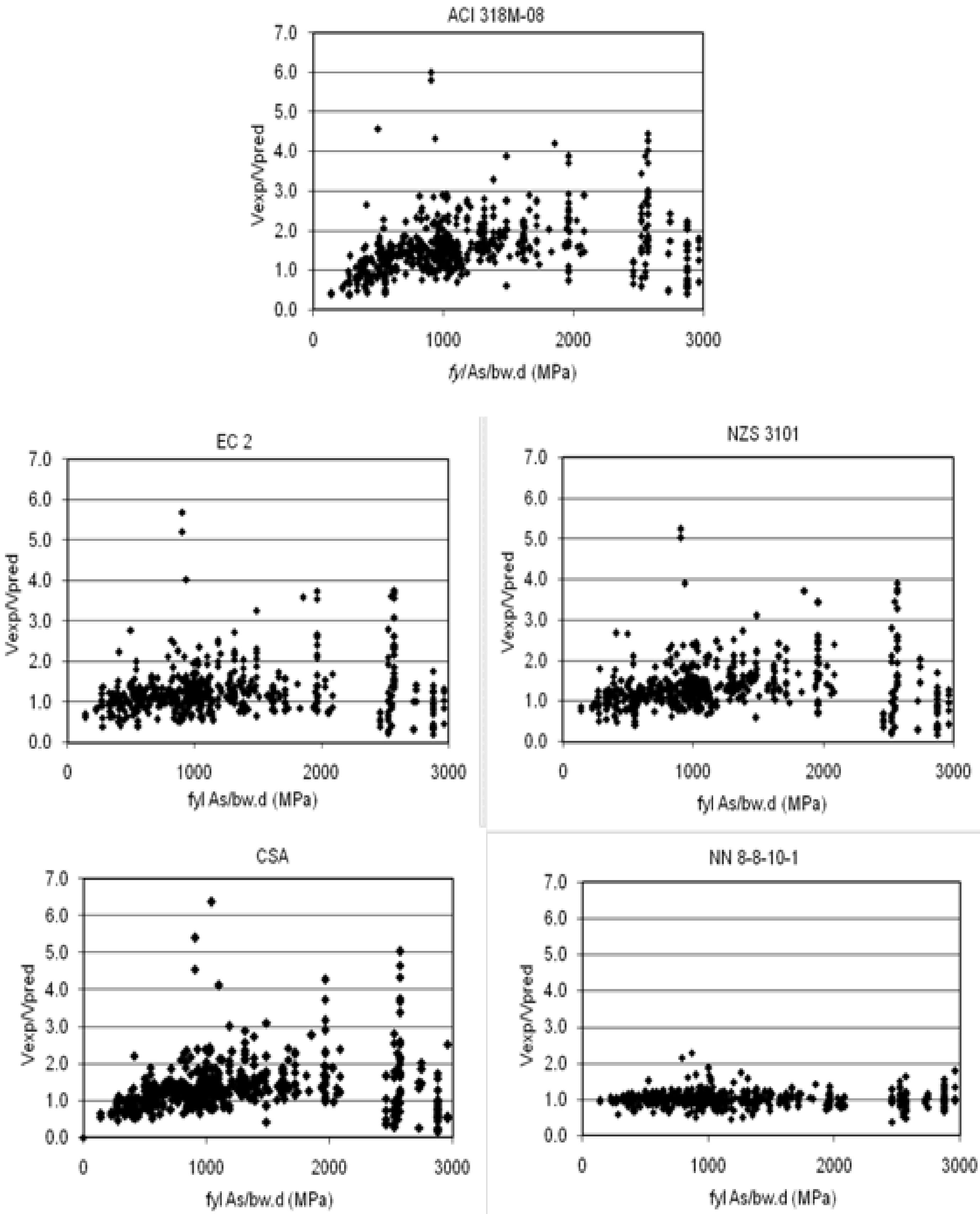


Figure 11. Experimental to predicted shear capacity versus $f_{yl}.\ \rho_l$ for different shear proposals.

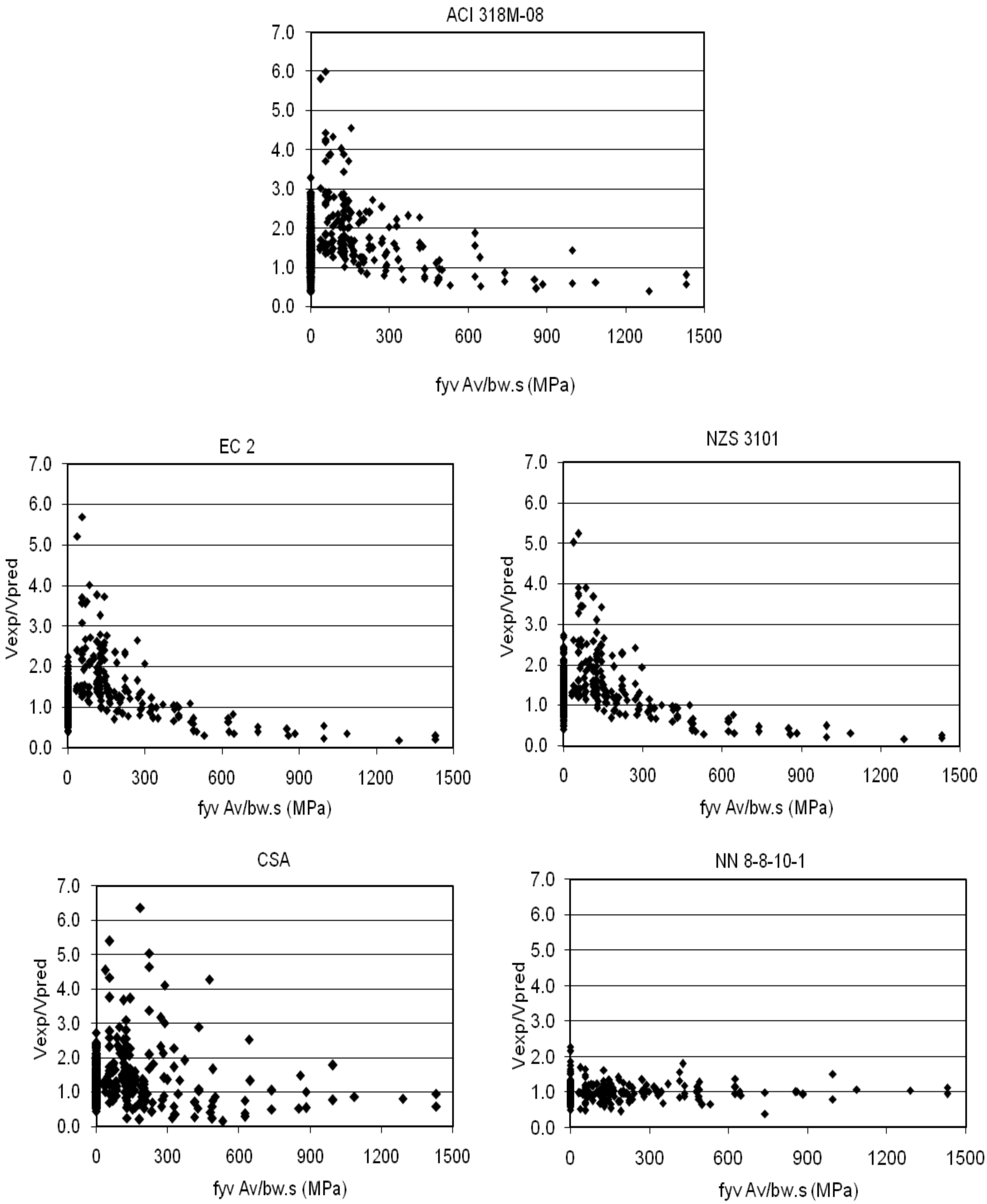


Figure 12. Experimental to predicted shear capacity versus fyv. ρv for different shear proposals.

the shear capacity. These effects are not properly captured by the examined codes. Also, the examined codes were observed to overestimate the effect of the shear reinforcement.

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