PREDICTING THE SHEAR STRENGTH OF REINFORCED CONCRETE BEAMS USING SUPPORT VECTOR MACHINE

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ABSTRACT

A wide range of machine learning techniques have been successfully applied to model different civil engineering systems. The application of support vector machine (SVM) to predict the ultimate shear strengths of reinforced concrete (RC) beams with transverse reinforcements is investigated in this paper. An SVM model is built trained and tested using the available test data of 175 RC beams collected from the technical literature. The data used in the SVM model are arranged in a format of nine input parameters that cover the cylinder concrete compressive strength, yield strength of the longitudinal and transverse reinforcing bars, the shear-span-to-effective-depth ratio, the span-to-effective-depth ratio, beam's cross-sectional dimensions, and the longitudinal and transverse reinforcement ratios. The relative performance of the SVMs shear strength predicted results were also compared to ACI building code and artificial neural network (ANNs) on the same data sets. Furthermore, the SVM shows good performance and it is proved to be competitive with ANN model and empirical solution from ACI-05.

Keywords : Support vector machine, Shear strength, Reinforced concrete.

ABSTRAK

Secara global teknik *machine learning* telah sukses diterapkan dalam berbagai model dari teknik sipil. Dalam makalah ini dibahas mengenai aplikasi dari *support vector machine* (SVM) untuk memprediksi gaya geser batas pada balok beton bertulang dengan tulangan geser. Model SVM dibuat untuk melatih dan menguji dari 175 data balok beton bertulang dari berbagai sumber. Data digunakan untuk membentuk 9 buah parameter dalam model SVM yaitu jarak dari muka balok ke titik berat tulangan tekan, tegangan leleh tulangan utama dan tulangan geser, rasio panjang geser dan tinggi efektif balok, dimesi penampang balok, dan tulangan utama serta tulangan geser balok. Hasil dari prediksi SVM akan dibandingkan dengan metode lain yaitu *artificial neural network* (AANs) dan ACI *Building Code* pada dataset yang sama. Selanjutnya, SVM menunjukan hasil yang baik dan terbukti dapat digunakan selain AANs dan rumus empiris ACI Building Codes.

Kata kunci : *Support vector machine*, Gaya geser, Beton bertulang.

1. INTRODUCTION

In designing a reinforced concrete (RC) beam, structural engineer must concern about the shear behavior of the RC beams. The shear failure of an RC beam is different from its flexural failure. In shear, the beam fails suddenly without warning and diagonal shear cracks are considerably wider than the flexural cracks. Shear failure is brittle and must be avoided in designing RC beams by providing the transverse reinforcement.

There are some parameters that affect the shear strength of RC beams including material strength, shear-span-to-effective-depth ratio, amount of reinforcement, etc. These parameters are used to predict shear strength of beams with an assumed form of empirical or analytical equation and are followed by a regression analysis using experimental data to determine unknown coefficients. But these equations in design codes do not accurately predict the shear strength of RC beams with transverse reinforcement and are also not easy-to-use types of equations.

This paper present the prediction of shear strength of RC beams with transverse reinforcement using support vector machine (SVM). The basic ideas underlying SVM are also reviewed in this paper, and its potential is demonstrated by applying the method on practical problems in civil engineering. In this study, the regression problems in SVM using support vector regression (SVR) will be used for modeling the experimental data. The results are then analyzed to determine the relative performance of SVM to that of artificial neural networks (ANNs) and the empirical shear design equations as given by American building code (ACI 318-05) on the same data sets.

2. ULTIMATE SHEAR STRENGTH OF RC BEAMS

The most shear design equations are derived from the equilibrium conditions of the simple 45o – truss theory proposed by Ritter and Morsch at the turn of the 20^{th} century.

These equations are in turn modified using statistical analysis to account for the effects of the flexure and the longitudinal reinforcement ratio on the shear strength of the RC beams.

ACI building code (American Concrete Institute, 2005) is one of the building codes that adopted this concept. The equations simply estimate the shear strength of an RC beams as the superposition of shear strength due to concrete alone and shear reinforcement alone.

However, the shear strength of RC beams predicted using these simple equations was found to be very conservative when compared to experimental observations. This was mainly because the equations were based on the assumption that there is no interaction between shear resisting mechanism.

The experimental data for the shear strength are already collected from the literature (Mansour et. al., 2004). There are total 175 RC beams with shear reinforcement from different literatures are tested with one or two point loads acting symmetrically with respect to the centerline of the beam span.

The data is shown in Table A1 in Appendix A. The beams have different support conditions simulating simple span, continuous span and fixed support conditions. During the collection stages, specimens that did not fail in shear were excluded from the database.

The important parameters that affect the shear strength of RC beams in this study are:

1. Shear-span (a)
2. Effective span of beam (L) and effective depth (d) of beam
3. Width of web (b_w)
4. Material strength of concrete, flexural (longitudinal) reinforcement and shear (transverse) reinforcement (f'_c, f_{yl}, f_{yt})
5. Reinforcement ratios of longitudinal steel and shear steel (ρ_l, ρ_t).

3. SHEAR STRENGTH USING ACI BUILDING CODE

For beams with transverse reinforcement, the ACI building code (American Concrete Institute, 2005), ACI 318-05 states that the nominal shear strength v_n of RC beams is the amount of concrete shear strength v_c and the transverse reinforcement v_s

$$v_n = v_c + v_s \tag{1}$$

where v_c and v_s are expressed as:

$$v_c = V_c/b_w d = \left(0.16\sqrt{f'_c} + 17.2\rho_w \frac{V_u d}{M_u}\right) \tag{2}$$

$$v_s = A_v f_{yv}/b_w s = \rho_v f_{yv} \tag{3}$$

In the above equation b_w is the breadth of beam, d is the effective depth of beam f'_c is the cylinder concrete strength of concrete, ρ_w is the longitudinal tensile reinforcement ratio, V_u and M_u are the shear strength and moment at critical section respectively, A_v is the area of vertical shear reinforcement, f_{yv} is the yield stress of stirrups, s is the spacing of stirrups and ρ_v is the shear reinforcement ratio. The ACI 318-05 (American Concrete Institute, 2005) also states that the concrete shear contribution and the shear reinforcement contribution must not be taken greater than $0.3\sqrt{f'_c}$ and $0.66\sqrt{f'_c}$ respectively.

4. ARTIFICIAL NEURAL NETWORKS (ANNs)

The first AAN was invented in 1958 by psychologist Frank Rosenblatt. Called Perceptron, it was intended to model how the human brain processed visual data and learned to recognize objects. Other researchers have since used similar ANNs to study human cognition. Eventually, someone realized that in addition to providing insights into the functionality of the human brain, ANNs could be useful tools in their own right. Their pattern-matching and learning capabilities allowed them to address many problems that were difficult or impossible to solve by standard computational and statistical methods. By the late 1980s, many real-world institutes were using ANNs for a variety of purposes.

ANNs are composed of many interconected processing units. Each processing unit keeps some information locally, is able to perform some simple computations, and can have many inputs but can send only one output. The ANNs have the capability to respond to input stimuli and produce the corresponding response, and to adapt to the changing environment by learning from experience. Therefore, in order for researchers to use ANNs as a predictive tool, data must be used to train and test the model to check its successfulness (Mansour et. al., 2004).

A key feature of neural networks is an iterative learning process in which data cases (rows) are presented to the network one at a time, and the weights associated with the input values are adjusted each time. After all cases are presented, the process often starts over again. During this learning phase, the network learns by adjusting the weights so as to be able to predict the correct class label of input samples. Neural network learning is also referred to as "connectionist learning," due to connections between the units. Advantages of neural networks include their high tolerance to noisy data, as well as their ability to classify patterns on which they have not been trained.

The most common neural network model is the multi-layer back-propagation neural networks (MBNNs) (Mansour et. al., 2004). Here the output values are compared with the correct answer to compute the value of some predefined error-function. By various techniques the error is then fed back through the network. Using this information, the algorithm adjusts the weights of each connection in order to reduce the value of the error function by some small amount. After repeating this process for a sufficiently large number of training cycles the network will usually converge to some state where the error of the calculations is small. In this case one says that the network has learned a certain target function. To adjust weights properly one applies a general method for non-linear optimization task that is called gradient descent. For this, the derivative of the error function with respect to the network weights is calculated and the weights are then changed such that the error decreases (thus going downhill on the surface of the error function). For this reason back-propagation can only be applied on networks with differentiable activation functions (Bishop, 1995).

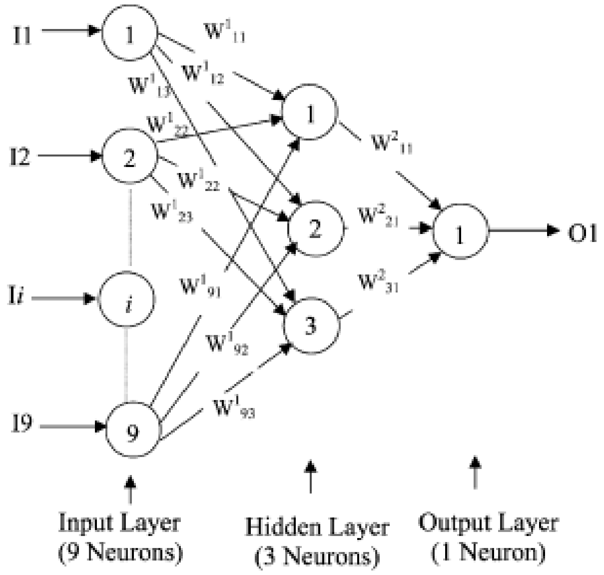


Fig. 1. A Typical MBNN (Mansour et. al., 2004)

The layout of the three-layer neural network used in this study is illustrated in Fig. 1. The network shown consists of an input layer with nine neurons, a hidden layer with three neurons, and an output layer with one neuron. The input layer neurons receive information from the outside environment and transmit them to the neurons of the hidden layer without performing any calculation. The hidden layer neurons then process the incoming information and extract useful features to reconstruct the mapping from the input space to the output space. Finally, the output layer neurons produce the network predictions to the outside world.

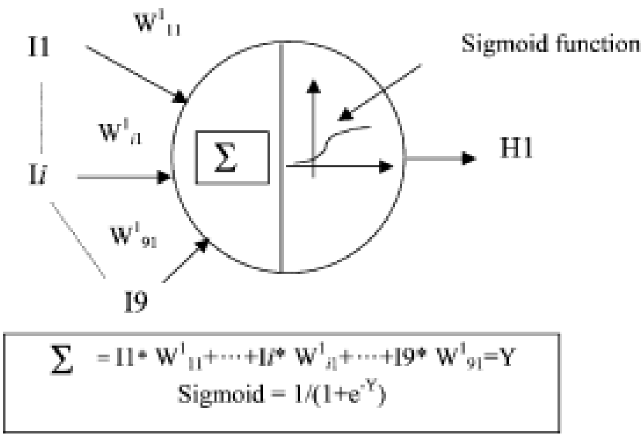


Fig. 2. Typical Neuron in a Hidden Layer (Mansour. et al., 2004)

To better explain the ANN procedure, the ANN network shown in Fig. 2 is taken as an example. The error ‘‘E’’ between the computed value (denoted by O_k) and the target output (denoted by T_k) of the output layer is defined as

$$E = \frac{1}{2}\sum_{k=1}^{n}(O_k - T_k)^2 \qquad (4)$$

where

$$O_k = F(I_i W_i^k) = F\left(\sum_{i=3}^{3} I_i W_i^k\right) \qquad (5)$$

In the equation above, $F(\ )$ is the sigmoid function defined in Fig. 2, I_i is the input to neuron ‘‘*k*’’ of the single output layer from neuron ‘‘*i*’’ of the hidden layer, and W_i^k is the weight associated between neuron ‘‘*i*’’ of the hidden layer and neuron ‘‘*k*’’ of the output layer. Note that in the ANN model shown in Fig.1, only one output is used and thus the subscript ‘‘*n*’’ in Eq. (4) (summation sign) is equal to 1. Therefore, from the hidden layer to the output layer, the modification of weights is represented respectively by the following expression:

$$\Delta W_i^k = \lambda \delta_k I_i \qquad (6)$$

where λ is the learning rate and $\delta_k = (T_k - O_k)\, F'\, (I_i\, W_i^k)$. From the input layer to the hidden layer, similar equations can also be written

$$\Delta W_i^k = \lambda \delta_j I_i \qquad (7)$$

where $\delta_j = W_k j \delta_k\, F'\, (I_i\, W_i^j)$.

The training algorithm can be improved by adding momentum terms into the weights equations as shown below:

$$W_i^k(t+1) = W_i^k(t) + \lambda \delta_k I_i + \gamma\left[W_i^k(t) - W_i^k(t-1)\right] \qquad (8)$$

$$W_i^j(t+1) = W_i^j(t) + \lambda \delta_k I_i + \gamma\left[W_i^j(t) - W_i^j(t-1)\right] \qquad (9)$$

where ‘‘*t*’’ denotes the learning cycle and ‘‘*c*’’ is the momentum factor.

5. SUPPORT VECTOR MACHINE (SVM)

The SVM is relatively new, the foundation of the subject of support vector machines (SVMs) has been developed principally by Vapnik and his collaborators, and the corresponding support vector (SV) devices are gaining popularity due to their many attractive features and promising empirical performance. It has demonstrated its good performance in classification (Osuna et. al., 1997; Belousov et. al., 2002), regression (Smola and Schölkopf, 1998; Dibike et. al., 2001), and time series forecasting and prediction (Mukherjee et. al., 1997; Muller et. al., 1997; Tay and Cao, 2001; Kim, 2003; Thissen et. al., 2003) in an efficient and stable way.

SVM formulation embodies the structural risk minimization (SRM) principle, which has been shown to be superior to the more traditional empirical risk minimization (ERM) principle employed by many of the other modeling techniques (Osuna et. al., 1997; Gunn, 1998). The SRM places an upper bound on the expected risk, as opposed to an ERM, which minimizes the error on the training data only. It is this difference that equips SVM with a greater ability to generalize compared to traditional neural network approaches. The SVM that will be used in this paper are ε - support vector regression (ε-SVR).

ε-SVR (Schölkopf and Smola, 1998) is an applied regression problem by the introduction of an alternative loss function that is modified to include a distance measure (Smola, 1996). Considering the problem of approximating the set of data, $\{(x_1,y_1), \dots (x_i,y_i), x \in R^N, y \in R\}$ with a linear function as expressed below:

$$f(x,\alpha) = \langle w.x \rangle + b \tag{10}$$

where w and b = parameters. With the most general loss function with an ε - insensitive zone described as:

$$\left|y_i - f(x,\alpha)\right|_\varepsilon = \varepsilon \text{ if } \left|y_i - f(x,\alpha)\right| \le \varepsilon \text{ ;}$$
$$\left|y_i - f(x,\alpha)\right| \qquad \text{otherwise} \tag{11}$$

The objective is now to find a function $f(x,\alpha)$ that has a most a derivation of ε from the actual observed targets y_i for all the training data at the same time as flat as possible. In performing nonlinear regression we map the input vector x into a high-dimensional feature space in which we then perform linear regression $f(z)$. The optimal regression function for primal problem is given by minimizing the functional of empirical risk.

$$\min_{w,b,\xi^{up},\xi^{down}} \tau(w,\xi) = \frac{1}{2}\|w\|^2 + \frac{C}{m}\sum_{i=1}^{m}\left(\xi_i^{up} + \xi_i^{down}\right) \tag{12}$$

where *C* is a parameter chosen a priori and defining the cost of constraint violation; and ξ_i^{up}, ξ_i^{down} = slack variables representing upper and lower constraints on the outputs of the system (Fig. 3), as follows:

$$y_i - \langle w, z_i \rangle - b \le \varepsilon + \xi_i^{up} \qquad \text{i = 1, 2, ….., m}$$

$$\langle w, z_i \rangle + b - y_i \le \varepsilon + \xi_i^{down} \qquad \text{i = 1, 2, ….., m}$$

$$\xi_i^{up} \ge 0 \text{ and } \xi_i^{down} \ge 0 \qquad (13)$$

The optimization problem can then be reformulated into an equivalent nonconstrained optimization problem using Lagrangian multiplier, and its solution is given by identifying the saddle point of the functional (Minoux, 1986). Lagrange function is constructed from both the objective function and the corresponding constraint by introducing a dual set of variables, as follows:

$$L(w, b, \xi^{up}, \xi^{down}, \alpha, \beta, \gamma, \delta)$$
$$= \frac{1}{2}\|w\|^2 + \frac{C}{m}\sum_{i=1}^{m}\left(\xi_i^{up} + \xi_i^{down}\right) + \sum_{i=1}^{m}\alpha_i\left[y_i - \langle w, z_i \rangle - b - \varepsilon - \xi_i^{up}\right]$$
$$+ \sum_{i=1}^{m}\beta_i\left[\langle w, z_i \rangle + b - y_i - \varepsilon - \xi_i^{down}\right] - \sum_{i=1}^{m}\gamma_i\xi_i^{up} - \sum_{i=1}^{m}\delta_i\xi_i^{down}$$
$$\alpha_i \ge 0,\ \beta_i \ge 0,\ \text{i = 1, 2, ….., m} \qquad (14)$$

where the α_i and β_i are the Lagrange multiplier. From the saddle point condition that the partial derivatives of the Langrangian has to be minimized with respect to w, b, ξ_i^{up} and ξ_i^{down} to vanish for optimality. Hence, we get the dual function as below:

$$W(\alpha) = -\frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{m}(\alpha_i - \beta_i)(\alpha_j - \beta_j)\langle z_i, z_j \rangle - \varepsilon\sum_{i=1}^{m}(\alpha_i + \beta_i) + \sum_{i=1}^{m}y_i(\alpha_i - \beta_i)$$

$$\alpha_i \ge 0,\ \beta_i \ge 0,\ \sum_{i=1}^{m}(\alpha_i - \beta_i) = 0,\ \text{i = 1, 2, ….., m} \qquad (15)$$

Therefore, the dual optimization problem will be:

$$\max_{\alpha,\beta}\left[-\frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{m}(\alpha_i - \beta_i)(\alpha_j - \beta_j)\langle z_i, z_j \rangle - \varepsilon\sum_{i=1}^{m}(\alpha_i + \beta_i) + \sum_{i=1}^{m}y_i(\alpha_i - \beta_i)\right] \qquad (16)$$

with respect to the constraints $\sum_{i=1}^{m}(\alpha_i - \beta_i) = 0 \qquad 0 \le \alpha_i, \beta_i \le \frac{C}{m}$ for i = 1, 2, ….., m

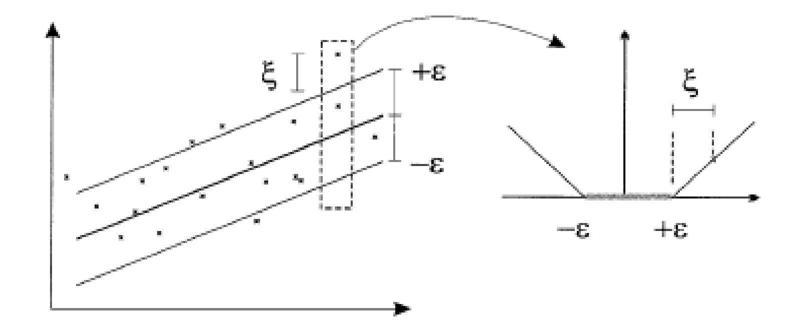


Fig. 3. Prespecified Accuracy and Slack Variable j in SV Regression, Adapted from Scholkopf (Scholkopf, 1997)

Finding the solution of (Mansour, et. al., 2004) for real-world problem will usually require application of quadratic programming and numerical methods. Once solution of the coefficients α_i and β_i are determined, the decision function can be found as:

$$f(x_{new}) = \left[\sum_{i=1}^{m}(\alpha_i^* - \beta_i^*)k\left(x_{new}, x_i\right)\right] + b^* \tag{17}$$

$$b^* = y_m - \varepsilon - \sum_{i=1}^{m}(\alpha_i^* - \beta_i^*)k\left(x_m, x_i\right) \tag{18}$$

where α^*, β^* are the solution of the dual problem and y_m and x_m are corresponding to SVs data. By using a nonlinear mapping kernel K is used to map the data into higher dimensional feature space, where the linear regression is performed.

6. ANN MODELS USED FOR PREDICTION OF SHEAR STRENGTH

In this study, ANN model for prediction the ultimate shear strength of RC beams with stirrups is develop by using XLminer with a fully integrated add-in to Microsoft Excel. It provides a comprehensive set of analysis features based both on statistical and machine learning methods. A problem or a data set can be analyzed by several methods. It is usually a good idea to try different approaches, compare their results, and then choose a model that suits the problem well. XLMiner uses Excel primarily as an interface and platform. While Excel limits the user to 60,000 rows, XLMiner allows the user to sample from a much larger database, do the analysis on a statistically-valid sample, and, for supervised learning, score the results back out to the database.

Using artificial neural network prediction in XLminer requires the following input data:

1. The error tolerance, which is set to 3%
2. The maximum number of training cycles or epochs is 600.
3. The total number of data that is 175 RC beams. In this study, the first 20% of the total data (already randomized in Excel) is used for testing and the remaining 80% for training.
4. The number of input neurons is nine, the number of output neurons is one, and the number of hidden layer neurons is three.
5. A learning rate (step size in gradient descent in Xlminer) and a momentum factor are equal to 0.4 and 0.2. In most of the simulations, it is found that one hidden layer and values of 0.4 for the learning rate and 0.2 for the momentum factor would lead to a minimum error.
6. Nine variables are used as input parameters for the ANN model constructed: (1) f'_c, (2) f_{yl}, (3) f_{yt}, (4) a/d, (5) b_w, (6) d, (7) L/d, (8) ρ_l, (9) ρ_t. The output was selected as the ultimate shear strength (V/b_wd) of the RC beam.
7. Normalized the input data (subtracting the mean and dividing by the standard deviation) to ensure that the distance measure accords equal weight to each variable. Without normalization, the variable with the largest scale will dominate the measure.

7. SVR MODELS USED FOR PREDICTION OF SHEAR STRENGTH

In this study, a computer program a library for support vector machines (Libsvm) will be used to develop an SVM model for predicting the ultimate strength of RC beams with stirrups. SVMs task usually involves with training and testing data which consist of some data instances. Each instance in the training set contains one "target value" and several "attributes" (features). The goal of SVM is to produce a model which predicts target value of data instances in the testing set which are given only the attributes. The Libsvm program procedures:

1. Features
   - The total number of data that is presented (in this case, 175 RC beams were considered). The computer program uses 80% of total data for training (140 RC beams) and the remaining 20% for testing (35 RC beams).
   - The nine variables of inputs are used for constructing the SVM model in this investigation are (1) f'_c; (2) f_{yl}; (3) f_{yt}; (4) a/d; (5) b_w; (6) d; (7) L/d; (8) ρ_l; (9) ρ_t.

- The one output in this study was selected as the ultimate shear strength (V/b_wd) of the RC beam.
- The input data are built using Ms. Excel (.xls) and imported to Matlab data (.mat). By using Matlab code, the data will be transferred to input format for Libsvm (.txt).

2. Scaling. Scaling the data before applying SVM is very important. (Sarle, 1997 ; Part 2 of Neural Networks FAQ) explains why we scale data while using Neural Networks, and most of considerations also apply to SVM. The main advantage is to avoid attributes in greater numeric ranges dominate those in smaller numeric ranges. Another advantage is to avoid numerical difficulties during the calculation. Because kernel values usually depend on the inner products of feature vectors large attribute values might cause numerical problems.
   The linearly scaling for this study is to the range [−1, +1] for each attribute.
3. Consider Kernel Function. There are four common kernels in Libsvm. For this investigation, radial basis function (RBF) kernel $k(x_i, x_n) = e^{-\gamma\|x_i - x_n\|^2}$ is used. The RBF kernel is used because nonlinearly maps samples into a higher dimensional space, the number of hyperparameters which influences the complexity of model selection (for example: The polynomial kernel has more hyperparameters than the RBF kernel), the RBF kernel has less numerical difficulties and can be used for every types of SVM and under every parameters.
4. Cross-validation and grid search. There are three parameter C, γ, ε to train the whole training set. It is not known beforehand which C and γ are the best for one problem; consequently some kind of model selection (parameter search) must be done. The goal is to identify good (C, γ) so that the regression can accurately predict unknown data (i.e., testing data).
   In v-fold cross-validation, we first divide the training set into v subsets of equal size. Sequentially one subset is tested using the classifier trained on the remaining v − 1 subsets. Thus, each instance of the whole training set is predicted once so the cross-validation accuracy is the percentage of data which are correctly classified. The cross-validation procedure can prevent the overfitting problem.
   For this study, the whole training data are divided into 10 set of equal size data. A "grid-search" on C, γ, ε using cross-validation is used also in this study.
5. Use the best parameter C, γ, ε to train the whole training set.
6. Test.

8. ANALYSIS RESULTS

The AANs model developed in this research is used to predict the shear strengths of the 35 RC specimens with the 140 RC specimens as training data. With that model, the predicted data have root mean square error (RMSE) = 1.1329 as can be seen in Table 1. The second generation (ε-SVR) of SVMs in regression are used to analyze the RC specimens. The SVM model developed in this research is used to predict the shear strengths of the 35 RC specimens with the 140 RC specimens as training data.

By using cross validation and grid search in Libsvm, the model can be able to learn the best value of C, γ, and ε. It is found that the best C value equal to 0.0625, the best γ value equal to 0.13149, and the best ε value equal to 0.2. By using those values, the cross validation and grid search minimize the training error, hence, the cross validation error mean square error reach 1.68.

The model is tested by predicting 35 RC specimens using svmpredict. The model use 87 numbers of data as SVs and 72 numbers of data as BSVs. With that model, the predicted data have root mean square error (RMSE) = 1.2265 as can be seen in Table 1. The ratio of SVM predicted shear strength to the experimental shear strength of each RC beam is given in Table 2. By using the ε-SVR, the average value of these ratios is 1.012.

Table 1. Root Mean Squares Error Values of Experimental to Predict Shear Strength

Method used	RMSE
ANN	1.1329
SVM	1.2265

The verification performance statistics, root mean square error (RMSE), is used to compare the AAN with SVM like in Table 1. RMSE statistics provide a general illustration of the overall accuracy of the predictions as they show the global goodness of fit. From the RMSE value, model with ANN provide a better general illustration of the overall accuracy of the predictions than model using SVMs.

The average value or mean and standard deviation of the experimental to predicted shear strength ratios of the data are used to verify the performance of all three models. The results can be seen in Table 2. Standard deviation is used to measure how spreads out the values in a data set are. More precisely, it is a measure of the average distance of the data values from their mean. If the data points are all close to the mean, then the standard deviation is low (closer to zero). In other hand, if many data points are very different from the mean, then the standard deviation is high (further from zero).

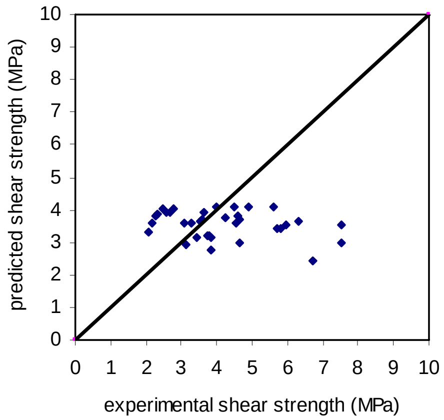
The SVM model developed in this study is used to predict the shear strength of the 35 RC beams. The ratio of SVM, ANN and ACI predicted shear strength to the experimental shear strength is given in Table A2 Appendix A. The mean value and standard deviation of the ratios predicted to experimental shear strength values for each method (only for testing data) also given in Table 2. From this table, we can see that the mean value of the ratios of predicted to experimental shear strength values of the testing data is 0.98 in ACI method, 1.083 in ANN method and 1.012 by using SVM. It means that SVMs method can predict the shear strength of the RC beams much better than the ACI building code method and the ANN method.

Table 2. Mean and COV Values of Experimental to Predict Shear Strength

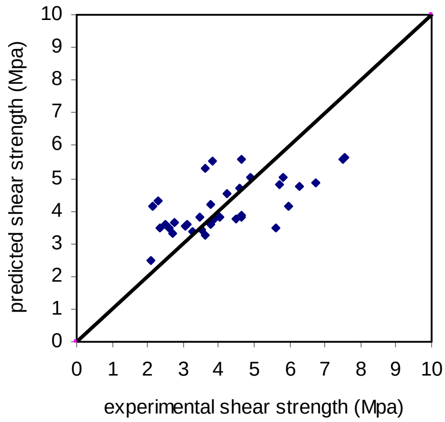
Method used	Mean	Std Dev
ACI	0.829	0.367
ANN	1.083	0.314
SVM	1.012	0.310

The SVM shear strength results as well as those obtained from ACI method and ANN method are shown in Fig. 4(a)-(c). It shows the predicted shear strength versus the experimental shear strength of the RC beams (only for testing data) for each method. The predicted results using the ACI building code method is seems to underestimate the observed shear strength of the RC beams as shown in Fig. 4(a), while the ANN model tends to predict the shear strength better than the ACI building code. It is shown in Fig. 4(b) that the observed shear strength of RC beams has variations on both side of the regression line, overestimate side and underestimate side. The predicted results using SVM model exhibit approximately the same trend for RC beams as the ANN model, but perform a little bit better than ANN model. It is shown by the mean value of the ratios of predicted to experimental shear strength value of the testing data in SVM method is smaller than in ANN method (Fig. 4(c)).

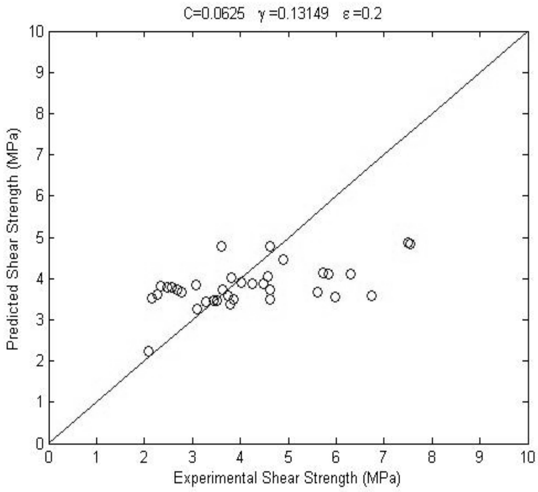
The SVM has the lowest standard deviation value and ACI has the biggest standard deviation value from the other model. That means the range predicted data to experimental data in ACI have very spreads out values in a data set than the other model. The result is shown in Table 2. From Fig. 4(a)-(c), the variation of all model data are very big. This phenomena is not good, the variation of predicted value to experimental value should be minimum. By using machine learning, the more training data, the more system can learn the performance of the data set. Therefore, to get the better prediction results, more data should be collected for training data.



(a) ACI (Mean=0.98)



(b) ANN (Mean=1.083)



(c) ε-SVR (Mean=1.012)

Fig. 4. Comparison of Predicted Shear Strengths versus Experimental Shear Strengths Using Various Methods

In overall, the performance of ANN and SVM is approximately the same and it predicted the shear strength value more accurately than ACI-05. Therefore, the SVMs can be used to predict the shear strength of RC beams with the transverse reinforcements.

By comparing the elapse time in both ANNs model and SVMs model, the performance of SVMs is much better than ANNs model. ANNs model needs 2 seconds to finish running the single input parameter of ANNs model (without cross validation error), while the SVMs model only need 0.77 seconds to finish the prediction without cross validation. The SVM exhibits inherent advantages due to its use of the structural risk minimization principle in formulating cost functions and of quadratic programming during model optimization. These advantages lead to a unique optimal and global solution compared to conventional neural network models.

9. CONCLUSION

The study conducted in this paper shows the feasibility of using support vector regression to predict the ultimate shear strengths of RC beams with transverse reinforcements. After learning from a set of selected training data, involving the shear strengths of transversely reinforced RC beams collected from the technical literature, the SVM model is used to successfully predict the shear strengths of the test data within the range of input parameters being investigated. Applying the SVM model to predict the shear strengths of RC beams with input parameters outside the range over which the model was trained does not guarantee adequate strength predictions. In such a case, more data should be collected to increase the range of input parameters needed to cover the domain of interest.

In this paper, the shear strength prediction by using three methods empirical equations, building codes from ACI-05, and machine learning techniques, ANN and SVMs, have been reviewed. It is found that the strength values obtained from SVM are more accurate than those obtained from design codes' empirical equations. The success of the SVMs model in predicting the shear strength of RC beams, within the input parameters used to train the model, rather than costly experimental investigation.

SVM training consists of solving a—uniquely solvable— quadratic optimization problem, unlike ANN training, which requires a nonlinear optimization with the possibility of converging only on local minima. Since the SVM is largely characterized by the type of its kernel function, it is necessary to choose the appropriate kernel for each particular application problem in order to guarantee satisfactory results.

The machine learning regression approach for shear strength prediction of RC beams with transverse reinforcements has also been demonstrated to provide a good alternative to the traditional use of conceptual modes. In particular, SVMs were found to generalize better by giving a more accurate prediction of runoff on test data.

Despite SVM's encouraging performance in this and other similar studies, several aspects still remain to be addressed. For example, determining the proper parameters C and ε are still a heuristic process, and automation of this process could be beneficial. The other limitations are those of computational speed and the maximum possible size of the training set relative to the available computer memory resource. But in general, SVMs provide an attractive approach to data modeling and have started to enjoy increasing popularity in the machine learning and computer-vision research communities.

This paper shows SVM potential as an alternative model induction technique for applications in civil engineering, especially in shear strength RC beams with transverse reinforcements.

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APPENDIX

Table A1. Data of Experimental Shear Strength

Beam	b (mm)	d (mm)	f'c (MPa)	fdy (MPa)	fty (MPa)	a/d	ρ(long) (%)	ρ(tran) (%)	L/d	vu-exp (MPa)	Code *
A2	178	381	29	515	357	2.50	3.81	0.19	5.0	4.57	V
E2A2(3-2)	152	318	19	305	345	2.23	2.67	0.37	8.2	3.11	V
R16	152	254	31	618	279	3.60	4.16	0.41	7.2	3.61	V
T13	152	272	13	618	269	3.36	1.46	0.21	6.7	6.74	V
D5-2	152	315	29	321	331	2.43	3.42	0.37	9.7	3.28	V
B2-1	203	390	23	321	331	1.95	3.10	0.73	4.7	3.80	V
B-120-030	200	352	35	931	1062	2.27	3.09	0.30	4.5	3.63	V
B-30-121	200	352	32	931	285	2.27	3.09	1.21	4.5	4.24	V
D4-3	152	315	22	321	331	2.43	3.42	0.49	9.7	3.45	V
G3	178	381	26	515	454	2.50	3.81	0.42	5.0	5.73	V
C3H2(2-6)	152	315	20	410	316	2.06	2.69	0.89	8.2	4.63	V
2-V1/4(2)	140	464	33	329	378	1.75	3.99	0.27	5.3	4.62	V
C2	178	381	28	515	357	4.25	3.81	0.19	8.5	5.98	V
B-1	231	461	25	555	325	3.94	2.43	0.15	7.9	2.09	V
1a-V3/8(14)	140	495	23	329	357	1.64	3.99	0.27	4.9	3.75	V
IID-2(13)	178	306	38	602	526	2.99	2.47	0.24	6.0	5.62	V
R14	152	272	29	618	269	3.36	1.46	0.14	6.7	2.16	V
G5	178	381	26	515	454	2.50	3.81	1.05	5.0	5.83	V
S10-M-2.0-36-40-1	200	336	29	854	830	2.38	2.88	0.40	4.8	3.07	V
E5	178	381	17	515	343	2.50	3.81	1.26	5.0	3.82	V
C305DO(5)	150	315	33	361	355	3.00	2.61	0.24	6.0	2.28	V
B-360-7.4	180	340	38	798	1422	1.76	3.16	0.44	3.5	4.49	V
T32	152	254	28	618	269	3.60	4.16	0.83	7.2	7.55	V
IIC-2(12)	178	310	38	576	526	2.96	4.38	0.24	5.9	4.90	V
B-1.5-110	200	352	35	931	841	2.27	3.09	0.58	4.5	2.58	V
B-360-4.1	180	340	38	798	1392	1.76	3.16	0.15	3.5	4.01	V
360-1.18	200	336	37	947	728	1.79	2.88	1.18	3.6	2.78	V
D2-6	152	315	30	321	331	2.43	3.42	0.61	9.7	3.52	V
J3	178	381	30	515	343	2.50	3.81	0.42	5.0	6.30	V
T9	152	254	20	618	279	3.60	4.16	0.41	7.2	7.50	V
360-0.89	200	336	37	947	728	1.79	2.88	0.89	3.6	2.48	V
R28	152	254	31	618	269	3.60	4.16	0.83	7.2	4.63	V
B-80-058S	200	352	34	931	841	2.27	3.09	0.58	4.5	2.34	V
B-120-059	200	352	35	931	1061	2.27	3.09	0.59	4.5	2.69	V
C2H1(3-8)	152	311	22	404	352	2.27	2.72	0.82	8.3	3.86	V
C4S3.0	220	244	42	402	358	3.00	3.60	0.22	6.0	3.47	T
A5	178	381	26	515	343	2.50	3.81	1.26	5.0	4.94	T
B-80-046	200	352	34	931	901	2.27	3.09	0.46	4.5	4.73	T
IV-o(34)	178	305	24	312	327	2.00	4.76	1.47	4.0	3.43	T
E4	178	381	13	515	343	2.50	3.81	0.79	5.0	8.33	T
D5-3	152	315	27	321	331	2.43	3.42	0.37	9.7	3.28	T
(2)-5	180	340	32	368	1324	1.76	3.21	0.28	3.5	4.89	T
(4)-9	180	340	20	795	1353	1.76	3.21	0.37	3.5	2.17	T
(2)-4	180	340	32	368	250	1.76	3.21	0.28	3.5	4.52	T

Table A1.*(continued)*											
B-80-022S	200	352	34	931	824	2.27	3.09	0.22	4.5	4.01	T
E2A3(3-3)	152	316	20	325	349	2.24	2.68	0.37	8.2	4.70	T
(4)-3	180	340	20	795	1275	1.76	3.21	0.12	3.5	2.09	T
B-30-046	200	352	33	931	349	2.27	3.09	0.46	4.5	3.34	T
(3)-4	200	336	23	1028	723	1.79	2.88	1.18	3.6	3.99	T
J5	178	381	32	515	343	2.50	3.81	1.26	5.0	3.85	T
B-150.019	200	352	35	931	1235	2.27	3.09	0.19	4.5	2.67	T
T11	152	254	37	618	279	3.60	4.16	0.41	7.2	4.60	T
C-2	152	464	24	555	325	4.93	3.66	0.20	9.8	2.30	T
210-0.40	200	336	23	1028	683	1.79	2.88	0.40	3.6	4.28	T
B-360-6.0	180	340	38	798	1333	1.76	3.16	0.31	3.5	5.29	T
A-2	305	464	24	555	325	4.93	2.28	0.10	9.9	1.73	T
(2)-11	180	340	32	368	255	1.76	3.21	0.75	3.5	2.64	T
C3H1(2-5)	200	352	33	931	866	2.27	3.09	0.19	4.5	2.96	T
B-60-030	200	352	33	931	492	2.27	3.09	0.30	4.5	4.49	T
T36	152	254	24	618	279	3.60	4.16	0.41	7.2	5.51	T
T34	152	254	34	618	269	5.40	4.16	0.21	10.8	4.03	T
1a-V1/4(13)	140	495	24	329	316	1.64	3.99	0.27	4.9	3.39	T
(4)-18	180	360	20	815	1275	1.76	0.61	0.12	3.3	5.58	T
A1-1	203	390	25	321	331	2.35	3.10	0.38	4.7	2.80	T
A3	178	381	30	515	343	2.50	3.81	0.42	5.0	5.26	T
T10	152	272	28	618	269	3.36	1.46	0.14	6.7	7.21	T
R8	152	272	27	618	269	3.36	1.46	0.21	6.7	1.92	T
B-120-121	200	352	35	931	1066	2.27	3.09	1.21	4.5	2.46	T
A4	178	381	28	515	343	2.50	3.81	0.79	5.0	5.82	T
T15	152	254	33	618	269	7.20	4.16	0.21	14.4	4.43	T
(3)-4	180	340	28	343	329	2.35	3.21	0.26	4.7	3.99	T
E2H2(3-7)	152	309	20	412	361	2.29	2.74	0.52	8.4	3.31	T
D4-1	203	390	23	321	331	1.95	3.10	0.37	4.7	3.51	T
E3H2(2-4)	152	326	25	395	314	1.99	2.60	0.89	7.9	2.90	T
S10-M-2.0-39-59-1	200	336	33	854	830	2.38	2.88	0.59	4.8	4.09	T
(4)-12	180	340	20	795	274	1.76	3.21	0.59	3.5	2.70	T
(2)-7	180	340	32	368	250	1.76	3.21	0.56	3.5	6.29	T
T19	152	254	30	618	269	5.40	4.16	0.21	10.8	6.24	T
T12	152	254	31	618	269	3.60	4.16	0.21	7.2	5.49	T
C2A2(3-5)	152	311	21	309	347	2.27	2.72	0.37	8.3	2.06	T
D4-1	152	315	27	321	331	2.43	3.42	0.49	9.7	3.51	T
(4)-16	200	336	21	854	830	2.38	2.88	0.89	4.8	2.93	T
B-360-5.1	180	340	38	798	1422	1.76	3.16	0.23	3.5	4.41	T
B1-2	203	390	25	321	331	1.95	3.10	0.37	4.7	3.23	T
B-360-11.0	180	340	20	798	1333	1.76	3.16	0.31	3.5	3.04	T
S10-M-2.0-36-89-1	152	254	33	618	269	7.20	4.16	0.14	14.4	4.00	T
(4)-10	180	340	20	795	285	1.76	3.21	0.26	3.5	5.66	T
B-80-121	200	352	34	931	898	2.27	3.09	1.21	4.5	3.82	T
R14	152	272	26	618	269	3.36	1.95	0.21	6.7	2.16	T
(3)-2	180	340	28	343	329	2.35	3.21	0.19	4.7	3.22	T
210-0.89	200	336	23	1028	723	1.79	2.88	0.89	3.6	5.69	T
D5-3	152	315	28	321	331	2.43	3.42	0.61	9.7	3.28	T

Table A1.*(continued)*

A1-4	203	390	25	321	331	2.35	3.10	0.38	4.7	3.08	T
D5-3	152	315	26	321	331	2.43	3.42	0.49	9.7	3.28	T
B-1.5-022	200	352	35	931	824	2.27	3.09	0.22	4.5	2.05	T
T7	152	264	27	618	269	3.46	3.00	0.21	6.9	5.94	T
B-360-11.0	203	390	25	321	331	1.95	3.10	0.37	4.7	3.04	T
A-1	307	466	24	555	325	3.94	1.80	0.10	7.8	1.63	T
210-0.59	200	336	23	1028	723	1.79	2.88	0.59	3.6	5.03	T
C4S3.5	220	244	42	402	358	3.50	3.60	0.22	7.0	3.05	T
B-120-019	200	352	35	931	1062	2.27	3.09	0.19	4.5	3.94	T
(2)-15	180	340	32	368	674	1.76	3.21	0.29	3.5	2.72	T
D1-8	152	315	28	321	331	1.94	3.42	0.46	7.8	3.88	T
T6	152	254	26	618	269	3.60	4.16	0.83	7.2	5.36	T
C4S3.5	152	315	28	321	331	2.43	3.42	0.37	9.7	3.05	T
B-360-11.0	180	340	38	798	1431	1.76	3.16	1.00	3.5	3.04	T
B-80-059	200	352	33	931	554	2.27	3.09	0.59	4.5	5.12	T
C3-1	203	390	14	321	331	1.56	2.07	0.34	4.7	2.82	T
(4)-12	152	254	31	618	269	3.60	4.10	0.21	7.2	2.70	T
C210DOA(3)	150	315	34	361	355	2.00	2.61	0.47	6.0	3.45	T
(2)-3	180	340	32	368	250	1.76	3.21	0.28	3.5	3.69	T
B-1.5-110	200	352	36	931	803	2.27	3.09	1.10	4.5	3.21	T
S10-M-2.0-36-89-1	200	336	29	854	830	2.38	2.88	0.89	4.8	4.00	T
S10-M-2.0-21-40-1	200	336	20	854	830	2.38	2.88	0.40	4.8	2.91	T
B-360-9.2	180	340	38	798	1402	1.76	3.16	0.71	3.5	2.40	T
(4)-7	180	340	20	795	1262	1.76	3.21	0.26	3.5	3.73	T
IA-2R(17)	178	306	18	602	526	2.99	2.47	0.24	6.0	4.64	T
(3)-4	140	464	24	329	378	1.75	3.99	0.27	5.3	3.99	T
G4	178	381	27	515	454	2.50	3.81	0.63	5.0	3.54	T
C4S2.0	220	264	42	402	358	2.00	2.67	0.32	4.0	3.75	T
IC-2R(19)	178	310	34	576	526	2.95	4.38	0.24	5.9	5.11	T
IIA-2(9)	178	306	18	602	526	2.99	2.47	0.24	6.0	3.78	T
B-120-019	178	381	28	515	343	2.50	3.81	0.42	5.0	3.94	T
D4-1	152	315	26	321	331	2.43	3.42	0.61	9.7	3.51	T
(4)-16	180	360	20	795	1275	1.76	1.20	0.12	3.3	2.93	T
B-2	229	466	23	555	325	4.91	2.43	0.15	9.8	1.88	T
T35	152	254	34	618	269	5.40	4.16	0.21	10.8	4.33	T
(4)-14	180	340	20	795	258	1.76	3.21	0.83	3.5	2.39	T
210-0.19	200	336	23	1028	683	1.79	2.88	0.19	3.6	2.85	T
C3-2	203	390	14	321	331	1.56	2.07	0.34	4.7	2.53	T
R24	152	254	31	618	269	5.05	4.16	0.21	10.1	2.38	T
D1-7	152	315	28	321	331	1.94	3.42	0.46	7.8	3.74	T
IV-n(333)	178	305	23	312	314	2.00	4.76	0.95	4.0	7.66	T
(2)-8	180	340	32	368	250	1.76	3.21	0.56	3.5	4.68	T
IC-2(5)	178	310	34	576	526	2.95	4.38	0.24	5.9	6.79	T
E3	178	381	14	515	343	2.50	3.81	0.42	5.0	7.52	T
E2A1(3-1)	152	318	25	313	345	2.23	2.67	0.37	8.2	5.41	T
2-V3/8(8)	140	464	28	329	329	1.75	3.99	0.27	5.3	4.91	T
T37	152	254	32	618	269	3.60	4.16	0.83	7.2	4.97	T
C2H2(3-9)	152	325	25	399	356	2.17	2.60	0.52	8.0	6.37	T

Table A1.*(continued)*											
B1-3	203	390	24	321	331	1.95	3.10	0.37	4.7	3.59	T
210-0.89	178	381	28	515	343	3.38	3.81	0.42	6.8	5.69	T
IA-2(2)	178	306	18	602	526	2.99	2.47	0.24	6.0	6.55	T
B-60-030	180	340	38	798	1422	1.76	3.16	0.44	3.5	4.49	T
C3H1(2-5)	152	316	20	412	316	2.05	2.68	1.11	8.2	2.96	T
D1-6	152	315	28	321	331	1.94	3.42	0.46	7.8	3.65	T
C205D10(2)	150	315	30	387	355	2.00	2.08	0.24	6.0	2.59	T
S10-M-2.0-21-40-1	150	315	29	361	355	2.00	2.61	0.24	6.0	2.91	T
(3)-2	200	352	34	931	803	2.27	3.09	1.10	4.5	3.22	T
(2)-11	203	390	24	321	331	2.35	3.10	0.38	4.7	2.64	T
(4)-9	155	464	30	555	325	3.94	1.80	0.20	7.9	2.17	T
B-120-019	178	306	34	602	526	2.99	2.47	0.24	6.0	3.94	T
C3-3	203	390	14	321	331	1.56	2.07	0.34	4.7	2.37	T
C4S4.0	220	244	42	436	358	4.00	3.60	0.22	8.0	2.65	T
E2H1(3-6)	152	324	21	400	347	2.18	2.61	0.82	8.0	3.30	T
T4	203	390	24	321	331	1.56	3.10	0.34	4.7	3.90	T
A1-3	203	390	23	321	331	2.35	3.10	0.38	4.7	2.81	T
360-0.19	200	336	37	947	679	1.79	2.88	0.19	3.6	2.55	T
B1-4	203	390	23	321	331	1.95	3.10	0.37	4.7	3.37	T
B-80-022S	180	340	20	798	1431	1.76	3.16	1.00	3.5	4.01	T
B-210-7.4	180	340	20	798	1422	1.76	3.16	0.44	3.5	4.81	T
S10-M-2.0-21-59-1	200	336	20	854	830	2.38	2.88	0.59	4.8	3.13	T
B-210-9.5	180	340	20	798	1402	1.76	3.16	0.71	3.5	5.35	T
C2A1(3-4)	152	318	23	304	353	2.23	2.67	0.37	8.2	2.52	T
R16	152	254	30	618	279	3.60	4.16	0.41	7.2	3.61	T
T4	152	272	32	618	269	3.36	1.95	0.21	6.7	3.90	T
(4)-5	180	340	20	795	1238	1.76	3.21	0.19	3.5	4.14	T
T8	152	254	31	618	269	3.60	4.16	0.21	7.2	6.57	T
R12	152	254	34	618	269	3.60	4.16	0.21	7.2	2.83	T
(2)-13	180	340	32	368	255	1.76	3.21	1.13	3.5	5.28	T
IIB-2(10)	178	308	17	581	526	2.97	1.41	0.24	5.9	4.77	T
C1-3	203	390	24	321	331	1.56	2.07	0.34	4.7	3.10	T
B-80-059	200	352	34	931	901	2.27	3.09	0.59	4.5	1.89	T
T14	152	254	33	618	269	3.60	4.16	0.83	7.2	7.68	T
C204-S0(30)	150	315	21	358	353	2.00	2.61	0.24	4.0	6.87	T

Table A2. Input data and prediction shear strength to experimental shear strength ratio

Beam	b (mm)	d (mm)	f'c (MPa)	fdy (MPa)	fty (MPa)	a/d	ρ(long) (%)	ρ(tran) (%)	L/d	Actual Value (vu-exp) (MPa)	ACI / Actual	ANN / Actual	ε-SVR/ Actual	ν-SVR/ Actual
A2	178	381	29	515	357	2.5	3.81	0.19	5.0	4.57	0.79	1.03	0.89	0.90
E2A2(3-2)	152	318	19	305	345	2.23	2.67	0.37	8.2	3.11	0.93	1.16	1.05	1.06
R16	152	254	31	618	279	3.6	4.16	0.41	7.2	3.61	1.03	1.47	1.33	1.37
T13	152	272	13	618	269	3.36	1.46	0.21	6.7	6.74	0.36	0.72	0.53	0.56
D5-2	152	315	29	321	331	2.43	3.42	0.37	9.7	3.28	1.10	1.02	1.05	1.04

Table A2.*(continued)*

B2-1	203	390	23	321	331	1.95	3.1	0.73	4.7	3.8	0.84	0.95	0.89	0.90
B-120-030	200	352	35	931	1062	2.27	3.09	0.3	4.5	3.63	1.09	0.90	1.03	1.01
B-30-121	200	352	32	931	285	2.27	3.09	1.21	4.5	4.24	0.89	1.07	0.92	0.91
D4-3	152	315	22	321	331	2.43	3.42	0.49	9.7	3.45	0.91	1.11	1.01	1.02
G3	178	381	26	515	454	2.5	3.81	0.42	5.0	5.73	0.59	0.84	0.72	0.74
C3H2(2-6)	152	315	20	410	316	2.06	2.69	0.89	8.2	4.63	0.64	0.82	0.75	0.76
2-V1/4(2)	140	464	33	329	378	1.75	3.99	0.27	5.3	4.62	0.83	0.84	0.81	0.81
C2	178	381	28	515	357	4.25	3.81	0.19	8.5	5.98	0.59	0.70	0.60	0.61
B-1	231	461	25	555	325	3.94	2.43	0.15	7.9	2.09	1.60	1.19	1.07	1.09
1a-V3/8(14)	140	495	23	329	357	1.64	3.99	0.27	4.9	3.75	0.85	1.12	0.96	0.97
IID-2(13)	178	306	38	602	526	2.99	2.47	0.24	6.0	5.62	0.73	0.62	0.65	0.64
R14	152	272	29	618	269	3.36	1.46	0.14	6.7	2.16	1.66	1.91	1.63	1.63
G5	178	381	26	515	454	2.5	3.81	1.05	5.0	5.83	0.58	0.86	0.71	0.72
S10-M-2.0-36-40-1	200	336	29	854	830	2.38	2.88	0.4	4.8	3.07	1.17	1.16	1.25	1.24
E5	178	381	17	515	343	2.5	3.81	1.26	5.0	3.82	0.72	1.45	1.05	1.10
C305DO(5)	150	315	33	361	355	3	2.61	0.24	6.0	2.28	1.68	1.90	1.58	1.56
B-360-7.4	180	340	38	798	1422	1.76	3.16	0.44	3.5	4.49	0.92	0.84	0.87	0.86
T32	152	254	28	618	269	3.6	4.16	0.83	7.2	7.55	0.47	0.75	0.64	0.67
IIC-2(12)	178	310	38	576	526	2.96	4.38	0.24	5.9	4.9	0.84	1.02	0.91	0.92
B-1.5-110	200	352	35	931	841	2.27	3.09	0.58	4.5	2.58	1.53	1.34	1.47	1.44
B-360-4.1	180	340	38	798	1392	1.76	3.16	0.15	3.5	4.01	1.03	0.95	0.98	0.98
360-1.18	200	336	37	947	728	1.79	2.88	1.18	3.6	2.78	1.46	1.32	1.32	1.27
D2-6	152	315	30	321	331	2.43	3.42	0.61	9.7	3.52	1.04	0.98	0.99	0.98
J3	178	381	30	515	343	2.5	3.81	0.42	5.0	6.3	0.58	0.76	0.65	0.67
T9	152	254	20	618	279	3.6	4.16	0.41	7.2	7.5	0.40	0.74	0.65	0.69
360-0.89	200	336	37	947	728	1.79	2.88	0.89	3.6	2.48	1.64	1.46	1.53	1.48
R28	152	254	31	618	269	3.6	4.16	0.83	7.2	4.63	0.80	1.21	1.03	1.07
B-80-058S	200	352	34	931	841	2.27	3.09	0.58	4.5	2.34	1.66	1.49	1.63	1.59
B-120-059	200	352	35	931	1061	2.27	3.09	0.59	4.5	2.69	1.47	1.23	1.38	1.34
C2H1(3-8)	152	311	22	404	352	2.27	2.72	0.82	8.3	3.86	0.81	0.98	0.91	0.92
										Mean	0.98	1.08	1.01	1.01
										Std dev	0.39	0.31	0.31	0.30