Evaluating punching shear strength of slabs without shear reinforcement using artificial neural networks

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Evaluating Punching Shear Strength of Slabs without Shear Reinforcement Using Artificial Neural Networks

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Synopsis: Punching shear failure of concrete slabs poses a significant risk in many concrete structures. This mode of failure can be brittle and catastrophic. The ability to accurately estimate the punching shear capacity of slab column connections in existing structures is essential, especially in evaluating the suitability to new loads added to a building. Punching shear has been studied, both experimentally and analytically. However, due to the number of parameters involved and the complexities in modeling, current approaches used to estimate the punching shear capacity of reinforced concrete (RC) slabs include mechanical models and design code equations. Mechanical models are complex, while design code equations are empirical. This study investigates the ability of artificial neural networks (ANN) to predict the punching shear strength of concrete slabs. The parameters considered to be the most significant in punching shear resistance of RC slabs were: concrete strength, slab depth, shear span to depth ratio, column size to slab effective depth ratio and flexure reinforcement ratio. Using a large and homogenous database from existing experimental data reported in the literature, the ANN model is able to predict the punching shear capacity of slabs more accurately than were the code design equations.

Keywords: reinforced concrete; punching shear; neural networks; design code.

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INTRODUCTION

Flat-plate structures are comprised of a slab with uniform thickness supported on columns with no beams or drop panels. This configuration makes flat-plate structures economically attractive due to its ease of construction. However, flat-plate structures are vulnerable to punching shear failure in the area surrounding the column due to a concentration of shear and bending in the slab. Punching shear failure of concrete slabs poses a significant risk in many concrete structures. This mode of failure is typically sudden and catastrophic. A local failure of the slab-column connection can initiate wider damage to the whole structure as previous experiences demonstrate (Gardner et al., 2002). Experiments indicated that the inclined crack leading to punching failure is initiated at the slab tension surface at a distance from the column face related to slab tensile reinforcement ratio: the higher tensile reinforcement ratio the larger the distance. For convenience, design codes specify a nominal critical section located at a distance of *0.5d* to *2d* from the column face, where *d* is the average slab effective depth. Generally, slab failure is associated with a truncated cone separating from the rest of the slab, whereupon the slab column connection is broken.

Analytical studies on punching shear behavior of RC slabs have been performed for some time, and several models are available in the literature. Two mechanical models have had some success in predicting the punching shear capacity of slabs: the Kinnunen-Nylander model (1960) and the Truss model (Alexander and Simmons, 1986) shown in Figure 1 and Figure 2, respectively. The Kinnunen-Nylander model is one of the most well recognized mechanical models for shear punching in slabs. It accounts for a crack that forms in the tension zone of the slab near the column due to flexure and which propagates toward the column and toward the compression zone. Any tensile reinforcement present in the slab tension zone provides resistance to the formation of this crack. The crack propagates most of the way through the depth of the slab, leaving only a small depth for the compression zone. This small depth exists in the column perimeter and is known as the "control surface". The control surface experiences shear with the slab pushing in the opposite direction with respect to the column. As the crack extends the control surface shrinks and the shear stress increases until the ultimate shear stress of concrete is reached. At this point the slab-column connection fails in a sudden and brittle manner.

To estimate the punching shear capacity of slab-column connections, an approach based on fuzzy-logic was used by Choi et al. (2007). A database consisting of 153 experimental datasets was used to train and test the fuzzy-logic system. It was noted that the model based on fuzzy logic produced more accurate predictions compared to existing code equations. Artificial neural networks (ANNs) have been used successfully in the past to estimate the shear capacity of RC beams (El-Chabib et al., 2006; Nehdi et al., 2006). The complexity of the parameters involved in shear behavior of RC beams made ANN an appropriate tool to tackle such a problem with success. For punching shear in slab column connections, a study by Bhatt and Agar (2000) used a radial basis network to predict the ultimate punching shear load for internal slab-column connections with no shear reinforcement. The database that was used consisted of 157 tests; the parameters considered were concrete strength, flexural reinforcement ratio, slab span, slab effective depth, yield stress of steel and column size. The ANN model was able to predict the punching shear capacity strength of slab-column connections more accurately that the British code BS8110-97. Another study conducted by Elshafey et al. (2011) used ANN to predict the punching shear capacity of slab-column connections. The ANN model that was able to outperform current code equations; this model used an extensive experimental database of 244 specimens and accounted for concrete strength, column size, flexural reinforcement ratio, slab effective depth and steel yield strength.

In this study, the use of ANN multi-layer perceptron networks (MLP) to predict the punching shear capacity of slab-column connections without shear reinforcement under concentric loading was investigated. An extensive, yet well filtered experimental database from published literature was used for that purpose. A comparison of the ANN model with existing design codes is presented and evaluated.

EXISTING CODE FORMULAS

Several studies formulated equations for punching shear strength calculations of slab-column connections. These include work done by Elstner and Hognestad (1956), Whitney (1957) and Moe (1961), some of which served as the basis for some design codes. Currently, existing code formulas for calculating punching shear strength in slabs without shear reinforcement are empirical and vary significantly in terms of their results. The majority of code formulas calculate the punching shear capacity of slab column connections as the product of stress capacity by the shear failure surface. The stress capacity usually is presented as a function of concrete strength (f'_c), while the failure surface is simplified to the product of the slab depth (d) and a critical shear perimeter at a distance between *0.5d* to *2d* from the column face. This critical shear perimeter is a square, circle, or square with rounded corners. Some codes account for tensile reinforcement, and some do not. In the following section, code formulas are represented.

ACI 318-08 (2008)

The equation of ACI 318-08 (2008) is more appropriate for design, in general. However, it does not account for longitudinal steel contribution to punching shear. The punching shear resistance of concrete, v_c, is given by the following equation:

$$v_c = 4\sqrt{f'_c} \quad \text{in U.S. Customary Units} \qquad (1a)$$

$$v_c = 0.33\sqrt{f'_c} \quad \text{in SI Units} \qquad (1b)$$

where f'_c is the cylinder compressive strength of concrete.

The critical shear perimeter is specified at *0.5d* from the column face and hence is equal to:

$$b_o = 4\,(c + d) \quad \text{for square columns} \qquad (2a)$$

$$b_o = \pi(c + d) \quad \text{for circular columns} \qquad (2b)$$

where c is the column size, specifically, the side width for a square column and the diameter for a circular column.

Eurocode 2 (2003)

The Eurocode 2 (2003) code formulation assumes that the punching shear resistance of RC slabs, $V_{RD,C}$, is proportional to the cubic root of the concrete strength. The equation accounts for the longitudinal reinforcement ratio. The punching shear stress capacity according to Eurocode 2 (2003) is calculated as:

$$v_{RD,C} = 5\,(100\rho f_{ck})^{1/3}\left(1 + \sqrt{\frac{7.9}{d}}\right) \quad \text{in U.S. Customary Units} \qquad (3a)$$

$$v_{RD,C} = 0.18\,(100\rho f_{ck})^{1/3}\left(1 + \sqrt{\frac{200}{d}}\right) \quad \text{in SI Units} \qquad (3b)$$

where d is the effective depth, ρ is the flexural reinforcement ratio, and f_{ck} is the characteristic compressive strength of concrete. The multiplier term involving d, is a factor to account for size effect. The critical shear perimeter, b_o, is defined at a distance *2d* from the column face with rounded corners and consequently equals:

$$b_o = 4\left(c + \pi d\right) \quad \text{for square columns} \tag{4a}$$

$$b_o = \pi\left(c + 4d\right) \quad \text{for circular columns} \tag{4b}$$

German Code DIN 1045 (2001)

In accounting for longitudinal reinforcement ratio and size effect, the German Code (DIN 1045, 2001) has a similar approach to Eurocode2, with some coefficients being slightly different. The punching shear stress capacity, $v_{Rd,ct}$, according to DIN 1045-1 (2001) is calculated as:

$$v_{Rd,ct} = 0.14\left(100\rho f_{ck}\right)^{1/3}\left(1 + \sqrt{\frac{7.9}{d}}\right) \quad \text{in U.S. Customary Units} \tag{5a}$$

$$v_{Rd,ct} = 0.14\left(100\rho f_{ck}\right)^{1/3}\left(1 + \sqrt{\frac{200}{d}}\right) \quad \text{in SI Units} \tag{5b}$$

The German code specifies the critical shear perimeter at *1.5d* from the face of the column with rounded corners and consequently equals:

$$b_o = 4c + 3\pi d \quad \text{for square columns} \tag{6a}$$

$$b_o = \pi\left(c + 3d\right) \quad \text{for circular columns} \tag{6b}$$

British Code BS 8110 (1997)

The BS 8110-97 defines the punching shear stress capacity as given by the following equation:

$$v_{BS} = 115\left(100\rho\frac{f_{ck,cube}}{3600}\right)^{1/3}\left(\frac{15.7}{d}\right)^{1/4} \quad \text{in U.S. Customary Units} \tag{7a}$$

$$v_{BS} = 0.79\left(100\rho\frac{f_{ck,cube}}{25}\right)^{1/3}\left(\frac{400}{d}\right)^{1/4} \quad \text{in SI Units} \tag{7b}$$

where d is the slab's effective depth, and ρ is the flexural reinforcement ratio. The multiplier term involving d, is used to account for size effect. The BS 8110-97 specifies the critical shear perimeter at *1.5 d* from the face of the column using the following equation:

$$b_o = 4\left(c + 3d\right) \quad \text{for square columns} \tag{8a}$$

$$b_o = \pi\left(c + 3d\right) \quad \text{for circular columns} \tag{8b}$$

ARTIFICIAL NEURAL NETWORK APPROACH

Artificial neural networks (ANNs) are highly adaptive data-driven, and trainable systems that are capable of capturing hidden and complex behavior through learning from training examples. The multi-layer perceptron networks (MLP) are the most widely used ANNs in engineering applications due to their ability 1) to implement non-linear transformations for functional approximation problems and 2) to map a given input(s) into desired output(s). Different from the traditional approaches, ANN cannot provide an explicit formulation. However, ANN can still be used for accurately predicting the performance of structural components based on existing experimental data. Additionally, as new specimens are tested, their test data can be easily added to the network database, thus continuously improving the model. The construction of an accurate artificial neural network involves several steps after the collection of a wide database. The first step is the normalization of the data, since the functions used in the ANN model accepts values from 0-1. Accordingly, the database first is normalized using the following equation:

$$x_t = \frac{(x - x_{\min})}{(x_{\max} - x_{\min})} \tag{9}$$

where x is the raw data value, x_t is the normalized value, and x_{min} and x_{max} are the minimum and maximum values of that particular parameter, respectively. After normalization the data is separated into training data and test data. For the current study, a random sample of about 20% of the data was used as testing data. The training data comprised the remaining 80%.

MLP networks consist of an input layer, an output layer and one or more hidden layers. Each layer contains a number of processing elements (units) that are partially or fully connected; the strength of each connection is represented by a numerical value called weight. Each unit manipulates input data in an effort to produce a specified output. This is done through providing the network with an input vector, and an output (target) vector. The input parameters are appropriately selected to have a significant relation to the output. The network is "trained" by using a set of data (training data) that contains input values and corresponding output values from the experimental data. The network iteratively processes the input data to reduce the error in its estimation of the output data. Each iteration involves processing data from the input layer to the output layer and comparing the output data produced by the network with the expected output data, which is the actual experimental data. In order to enhance the accuracy of the following iteration, the difference, or error, between the calculated output and actual output is used to adjust the assigned weight to the links. The network configures the weight by assigning each link an initial value, then adjusting this value based on the back-propagation errors. The links of the network, or transfer functions, that are described above, are log-sigmoid functions of the form:

$$f(U) = \frac{1}{1 + e^{-\beta U}} \tag{10}$$

where β is a constant.

After training, the network is tested for accuracy. Testing data, which is a set of input-output pairs that have not been processed by the neural network, is used to check the accuracy of the network. The average absolute error (*AAE*) between predicted and measured values is used as the acceptance criterion. The average absolute error is defined using the following equation:

$$AAE = \frac{1}{n}\sum \frac{\left|V_{\exp} - V_{pred}\right|}{V_{\exp}} \times 100 \tag{11}$$

where V_{exp} and V_{pred} are the measured and predicted punching shear ultimate load for a given specimen, respectively. A more detailed explanation of the training process can be found elsewhere (Hayken, 1994; El-Chabib and Nehdi, 2005). It is noted that, as a statistics-based approach, ANN models perform best within the range of parameters used to train it. Accordingly, cautions must be exercised when such models outside the range of original parameters are used.

EXPERIMENTAL DATABASE

Although several parameters contribute to the success of training a MLP network, the learning material provided for the training remains the most important factor that affects the network's performance and generalization. A more comprehensive learning material is likely to provide better network generalization and assist in capturing the embedded relationships between inputs and corresponding outputs. In order to capture the embedded relationships between the most influential parameters of RC interior slab-column connections and their corresponding punching shear capacity, it is essential to train a neural network model on a comprehensive and sufficiently large shear database. In this study, punching shear strength results for 153 slab-column connections, with no shear reinforcement, failing in shear under monotonic loading were considered from an initial 205 specimen collected from the literature (Appendix A). The elimination of the some test results from the database was designed to homogenize the dataset and to help improve the capacity of the ANN model in predicting the punching shear capacity of slab-column connections. In the following section, the criteria used for elimination is discussed.

Predominant shear failure

Specimens with predominant flexure behavior were eliminated. The criterion for elimination was set at V_u/V_{flex} >1. Typically, specimens with predominant flexure behavior exhibit high deflection prior to shear failure resulting in shear failure at lower than maximum load. A study by Criswell (1974) supports such criterion since the reduction of longitudinal reinforcement is associated with increased ductility and subsequently a reduction in connection strength, as shown in Figure 3 . Furthermore, Regan and Braestrup (1985) suggested that since punching is likely caused prematurely by excessive flexure, punching shear analysis is unnecessary if the failure load is similar to the flexural capacity of the slab. Also, specimens were eliminated that had reported bond slip failure.

Flexural reinforcement uniformity

Specimens with higher concentration of reinforcement directly over the column and extending out from the four column faces were also eliminated since this may affect the uniformity of results.

Column shape

All column-slab connections considered in this study involved square or circular columns (b/c = 1). The punching shear capacity of the slab-column connection can be reduced for oddly shaped columns, especially those with b/c > 2.

Size limitations

Specimens with slabs that were judged to be too thin were eliminated. This criterion resulted in excluding specimens with slab thinner than 2.75 in (70 mm). Specimens thicker than 8 in. (200 mm) were also excluded since there is a limited number of tests with such thickness.

Final dataset

After applying the established elimination criteria, the original number of 205 specimens was reduced to 153. The final data set was split into “training data” and “testing data” in order to run the neural network. The training data set contained 122 specimens and the testing set contained 31 specimens. Specimens were selected for the testing data set by randomly choosing a few from each experimental program. Such practice is adopted based on previous experience of using ANN to model the performance of RC structural members (El-Chabib et al., 2005 and 2006). The number selected was proportional to the total number of specimens tested by that same experimental program. This was done to account for such differences as laboratories used, testing conditions, and test setting. This approach is based on previous experience

The database was compiled in a patterned format. Each pattern consisted of an input vector containing the geometrical and mechanical properties of RC interior slab-column connections, and an output vector containing the corresponding punching shear capacity of the slab. The range of parameters for these slabs is given in Table 1. The first five rows represent the “input parameters”, which the neural network uses to predict the “output parameter”. In this case, the output parameter is the specimen’s ultimate load, V_{ult}. A discussion of the selection of input parameters is found in the ANN Model section.

ANN MODEL

Selection of Parameters

For the analysis of punching shear capacity of RC slabs several parameters were of interest. Previous studies considered various geometric and material parameters influencing the punching shear capacity of slab-column connections. However, in this study five parameters -- concrete strength (f'_c), slab effective depth (d), shear span to depth ratio (a/d), column size to slab depth ratio (c/d) and flexural reinforcement ratio (ρ) -- were selected. The choice of dimensionless parameters helps generalize the ANN model usage, other parameters help with such aspects as size effect. In the following section, a discussion of the choice of parameters is presented.

Concrete compressive strength — is considered by all code equations, accordingly, was accounted for in the ANN model. Concrete strength is used at a square or cubic root to represent the concrete tensile capacity, which governs diagonal tension.

Slab average effective depth — is used by some code equations to account for size effect. Several studies (Bazant and Cao, 1987; Broms, 1990) indicated that size influences the strength of concrete slabs in punching. The effective depth used was an average of the effective depth for flexural reinforcement in two directions.

Shear span to depth ratio — was selected as a dimensionless parameter to account for the interaction between shear and flexure. After cracking, the compression zone provides a significant part of the punching resistance throughout its depth. Previous studies (Reagan and Braestrup, 1985) indicated that there is a significant interaction between shear and flexure.

Column size to slab depth ratio — was considered by some studies to be a relevant factor (Moe, 1961); however, no code equation considers this factor directly. Nonetheless, column size is a parameter in all code equations for critical shear perimeter calculation.

Flexural reinforcement ratio — is accounted for since steel contributes to punching shear resistance through dowel action. Reinforcement also controls cracking width and depth, and hence affects the punching shear capacity of slab-column connections. Several codes account for the flexural reinforcement ratio.

Because specimens with predominant flexural behavior were excluded in this study, the yield stress of steel reinforcement was not considered. This is justified by the fact that those specimens will not sustain significant flexural yielding before brittle punching shear failure occurs. Also, compression reinforcement in the slab was neglected in this study.

ANN Architecture

In this study, several ANN architectures were tested to develop a feed-forward back-propagation MLP network that can accurately predict the punching shear strength of RC interior slab-column connections. The ANN model utilized a scaled gradient conjugant (SGC) function, contained within MatLAB, Neural Network Toolbox. The variables that were investigated included the optimum number of epochs and the number of neurons in one hidden layer. An epoch or single pass of the data through the network created an error output, between the network's predicted output and desired output. The architecture that was adopted for the final network consisted of an input layer containing five variables representing punching shear design parameters, an output layer with one unit representing the punching shear capacity (V_{ult}), and a hidden layer of eight processing units (Figure 4). A tangent sigmoid transfer function had the best performance with the chosen ANN model architecture. The optimum number of epochs was found to be between 140 to 150 epochs, the learning curve is shown in Figure 5. The performance criterion for network selection was the minimum average absolute error. The ANN was trained using 122 data patterns, and was tested on the remaining 31 patterns to verify whether the network was appropriately trained and able to capture the relationship between the different input parameters and output. The testing patterns were randomly selected from the original database, and were not used in the training process.

RESULTS AND DISCUSSION

The current study evaluated the performance of four code equations, namely ACI 318-08 (2008), Eurocode2 (2003), DIN 1045 (2001) and BSS8110 (1997) as well as an ANN model. The performance of different approaches investigated in this study was evaluated using the testing database as described earlier. It is worth noting that the selection criteria limits the final dataset to a subset of punching geometries and loading conditions that enhances the capability of the ANN model to estimate the punching shear strength. In contrast, the code based approaches are formulated to work in the conservative realm in a much larger set of problems that still ensure ductile failure. Accordingly, comparing the performance of code equations versus the ANN model should be viewed within this context.

The estimated punching shear capacities subsequently were compared to the experimentally measured values. The performance of the each approach was evaluated based on the average absolute error (*AAE*) and a performance factor calculated using the following equation:

$$PF = \frac{V_{\exp}}{V_{pred}} \tag{12}$$

The average, the standard deviation (*STDV*), and the coefficient of variation (*COV*) for the performance factor (*PF*) and average absolute error (*AAE*) of the ANN model as well as the four design codes approaches discussed earlier are listed in Table 2. Initial examination of the design codes approaches shows a striking conceptual similarity. However, the differences in handling the critical shear perimeter and coefficients demonstrate their deep empirical foundations. The logical explanation for such variation is that different researchers interpret sub-sets of test data to formulate code equations, keeping in mind prevailing reinforcement practices in their respective countries. Nonetheless, a design code is a complex set of evolving rules and guidelines that are gradually calibrated over time to give acceptable results. Results shown in Figure 6 and Table 2 demonstrate a mostly conservative approach for codes' approaches, except for Eurocode 2 (2003). The results indicate that among all code equations, the ACI 318 approach, despite being the least accurate, has produced the most conservative results. This can be attributed to the fact that ACI 318 (2008) equation does not account for flexural reinforcement and size effect, yet it needs to remain conservative in its simplistic form. Furthermore, specimens with capacity higher than 800 kN, mostly with 200 mm thick slab and high strength concrete, have significantly larger error compared to other specimens. This points out that the terms accounting for concrete and for size effect should be revisited, especially with current trends in construction favoring high strength concrete. High strength concrete has inherently lower shear capacity since its cracks propagate across coarse aggregate rather than around them making aggregate interlock less effective (El-Chabib et al., 2006).

Figure 7 illustrates the ANN predicted punching shear capacities of RC slab-column connections under monotonic loading versus the corresponding experimentally measured ones. It can be observed that the data points for the ANN are the closest to the equity line compared to other code equations shown in Figure 6. The ANN model was able to predict the punching shear strength of RC slab-column connections more accurately than the studied code equations. The

CONCLUSIONS

This study investigated the feasibility of using artificial neural networks as an alternative method for predicting the punching shear capacity of RC slab-column connections under monotonic loading and without shear reinforcement. A large number of ANN architectures were investigated to find the optimum ANN configuration . The study compared the ANN model predictions to those of several existing design codes equations. The ANN approach can be used as an effective method to predict the punching shear capacity of slabs. This approach outperformed all other methods considered in this study and reasonably predicted the punching shear capacity of slabs with a wide range of geometric and material parameter properties. The approach that design codes use to account for concrete strength should be thoroughly reexamined since current trends are shifting towards the use of high strength concrete.

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Table A1 – Main characteristics of the specimens included in the used database

Specimens	Reference	Concrete Strength ksi (MPa)	Average Reinforcement Depth In. (mm)	Reinforcement Ratio (%)	Punching Shear Strength kips (kN)
6	Alexander & Simmonds (1992)	3.8-5.1 (26-35)	4.2-5.2 (106-133)	0.50-0.82	58-72 (257-319)
15	Bernaert & Puech (1966)	2.0-5.9 (14-41)	4.0-4.9 (102-124)	1.00-1.90	56-122 (247-541)
4	Chen & Li (2005)	2.5-4.9 (17-34)	2.8 (70)	0.59-1.31	23-51 (104-226)
2	Corley& Hawkins (1968)	6.4 (44)	4.4 (111)	1.00-1.50	60-75 (266-334)
8	Criswell (1974)	3.9-5.2 (27-36)	4.8-5.0 (121-127)	0.75-1.56	61-131 (273-581)
3	Ebead & Marzouk (2004)	4.4-5.2 (30-36)	4.3-4.5 (109-114)	0.35-1.00	56-94 (250-420)
24	Elstner & Hognestad (1956)	1.6-6.1 (11-42)	4.5-4.8 (114-121)	0.50-6.90	40-130 (178-578)
4	Kinnunen & Nylander (1960)	3.8-4.2 (26-29)	4.6-5.0 (117-128)	0.80-1.10	57-97 (255-430)
5	Lovrovich & McLean (1990)	5.7 (39)	3.3 (83)	1.70	29-108 (129-480)
14	Marzouk & Hussein (1991)	6.1-11.6 (42-80)	2.8-4.9 (70-125)	0.50-2.10	56-145 (249-645)
2	McHarg et al. (2000)	4.4 (30)	4.3 (109)	1.10-1.23	69-81 (306-360)
12	Moe (1961)	3.0-4.1 (21-28)	4.5 (114)	1.10-1.50	70-97 (312-433)
15	Ramdane (1996)	4.1-14.8 (28-102)	3.9-4.0 (98-102)	0.60-1.30	38-91 (169-405)
23	Regan (1986)	1.4-6.4 (10-44)	2.8-7.9 (70-200)	0.80-1.50	24-185 (105-825)
3	Swamy & Ali (1982)	5.7 (39)	3.9 (100)	0.37-0.74	29-50 (131-222)
4	Theodorakopoulos & Swamy (1993)	5.1-5.4 (35-37)	3.9 (100)	0.37-0.56	31-43 (137-191)
9	Yitzhaki (1996)	1.5-3.0(10-21)	3.2-3.2(80-82)	0.70-2.00	22-55 (98-244)

Table 1- Range of shear design parameters and V_{ult} for the slabs included in the database

Parameters	Minimum	Maximum	Average
f'_c ksi (MPa)	1.39 (9.6)	14.84 (102.3)	5.60 (38.6)
d in. (mm)	2.76 (70)	7.87 (200)	4.61 (117)
a/d	1.80	13.6	6.61
c/d	0.46	4.21	1.80
ρ (%)	0.40	6.90	1.42
V_{ult} kip (kN)	22 (98)	185 (825)	90 (401)

Table 2- Performance of ANN model and various punching shear methods in predicting the strength of slabs.

Approach	*AAE*	V_{exp}/V_{pred}		
		Average	*STDV*	*COV*
ANN	9.12%	1.03	0.07	7.58
ACI 318-08	51.20%	1.49	0.36	24.2
Eurocode2	16.10%	0.86	0.15	17.2
DIN 1045-1	34.74%	1.33	0.23	17.6
BSS8110-97	31.04%	1.27	0.30	23.4

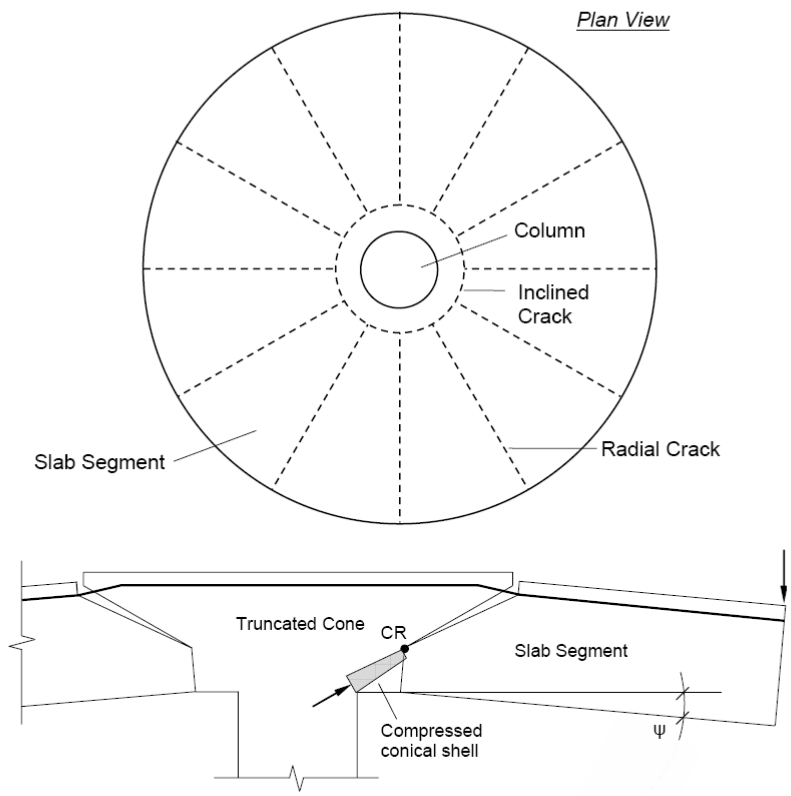


Figure 1. Kinnunen and Nylander's model (1960).

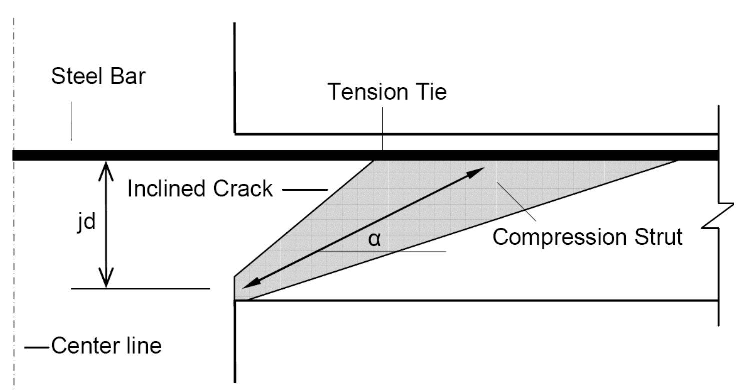


Figure 2. Truss model (Alexander and Simmonds, 1986).

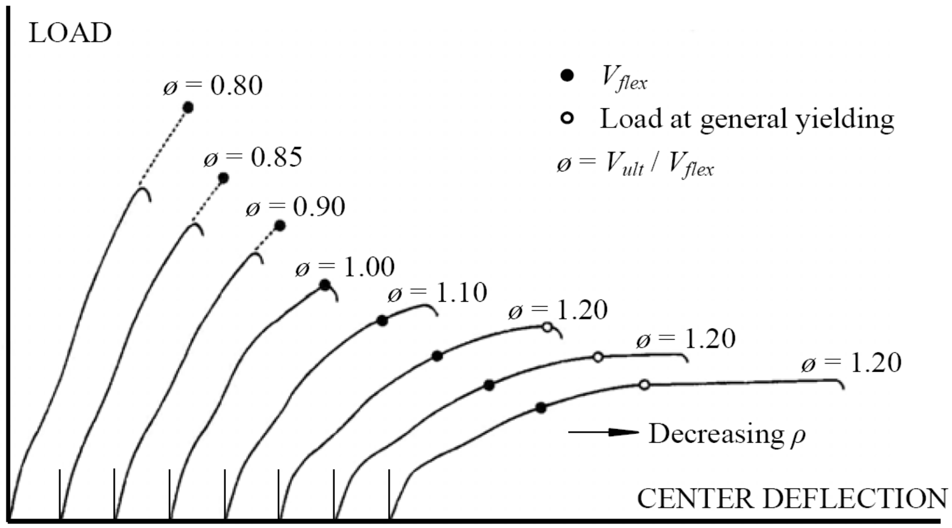


Figure 3. Typical behavior of slab-column connections under monotonic concentric Load, with increased ductility at lower flexural reinforcement ratios. (Criswell 1974)

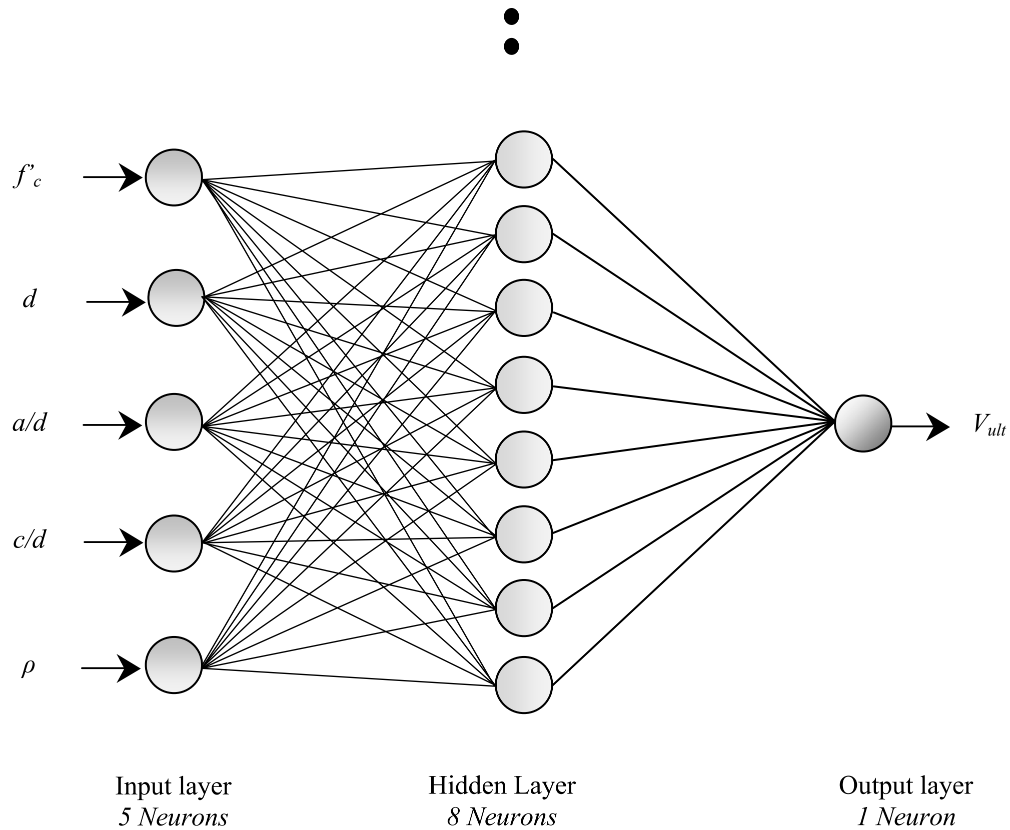


Figure 4. The neural network model used in this study

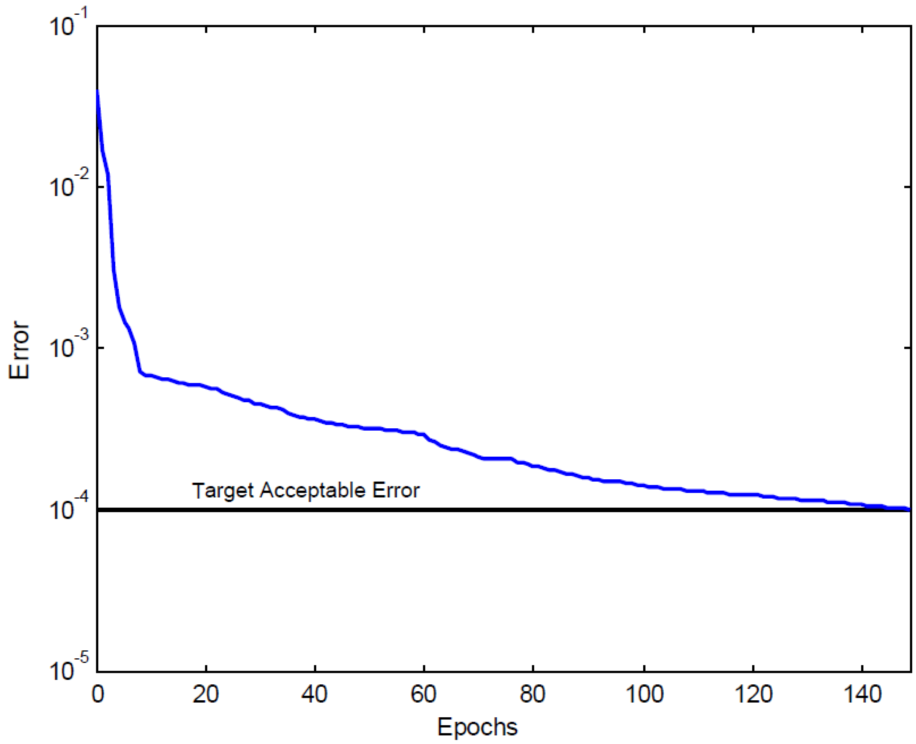
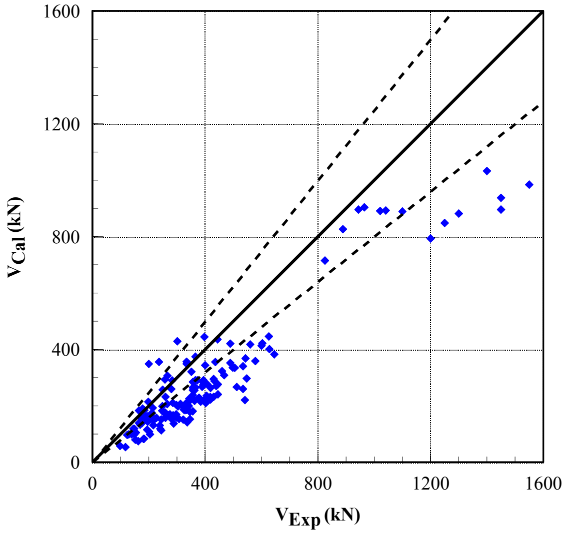
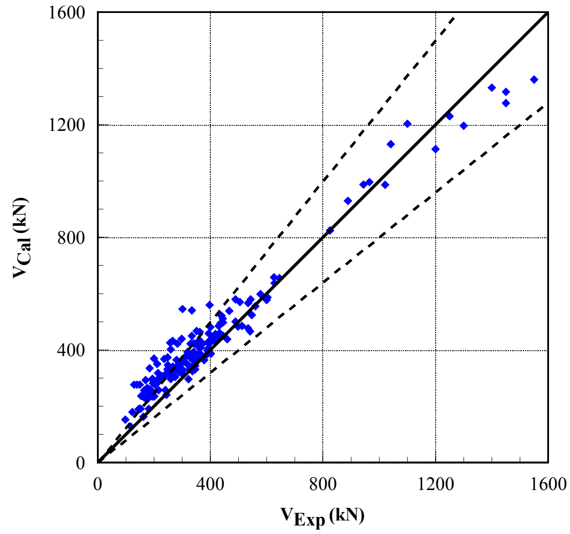


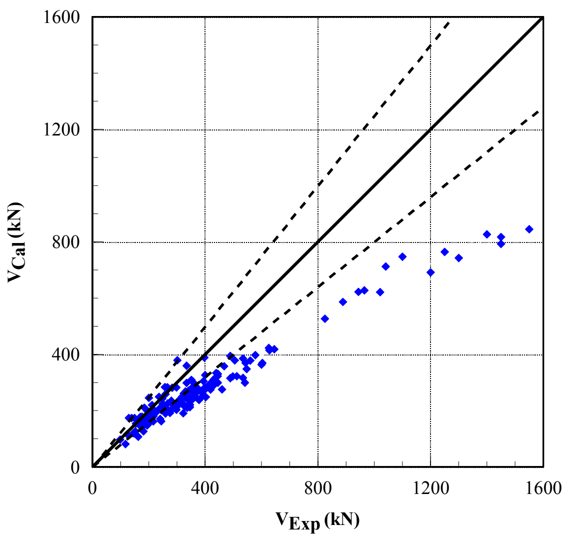
Figure 5. The learning curve of the ANN model showing convergence



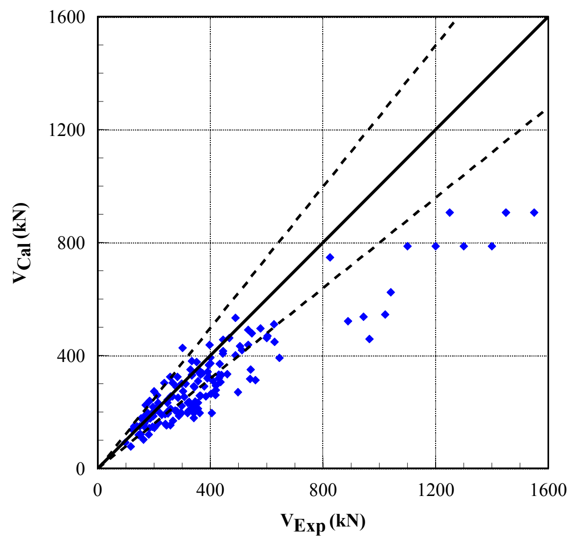
(a) ACI 318 (2008)



(b) EC2 (2003)



(c) DIN 1045 (2001)



(d) BSS 8110 (1997)

Figure 6. Performance of code equations in calculating the punching shear capacity of concentrically loaded slab-column connections.

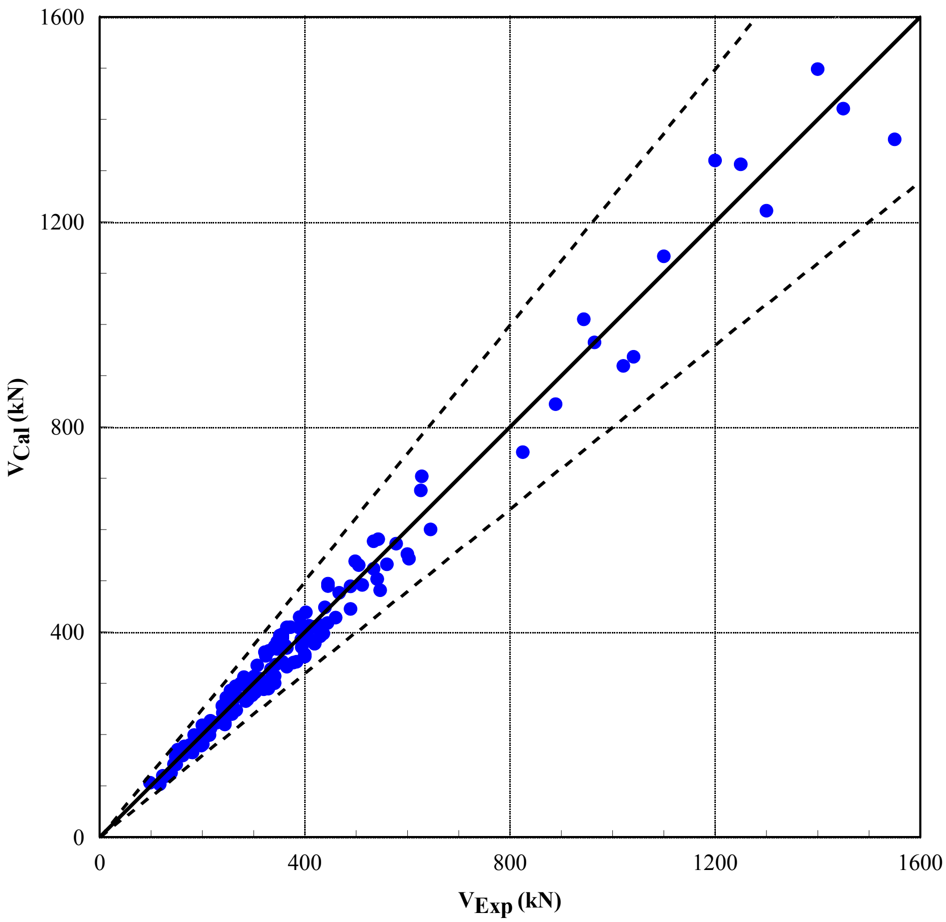


Figure 7. Performance of the ANN model in calculating the punching shear capacity of concentrically loaded slab-column connections.