An Adaptive Neuro-Fuzzy Inference Model to Predict Punching Shear Strength of Flat Concrete Slabs

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Abstract: An adaptive neuro-fuzzy inference system (ANFIS)-based model was developed to predict the punching shear strength of flat concrete slabs without shear reinforcement. The model was developed using a database collected from 207 experiments available in the existing literature. Five key input parameters were used to build the model, which were slab effective depth, concrete strength, reinforcement ratio, yield tensile strength of reinforcement, and width of square loaded area. The output parameter of the model was punching shear strength. The results from the adaptive neural fuzzy inference model were compared to those from the simplified punching shear equations of ACI, BS-8110, Model Code 2010, Euro-Code 2, and also experimental results. The root mean square error (RMSE) and the correlation coefficient (R) were used as evaluation criteria. Parametric studies were presented using ANFIS to assess the effect of each input parameter on the punching shear strength and to compare ANFIS results to those from the equations proposed in commonly used codes. The results showed that the ANFIS model is simple and provided the most accurate predictions of the punching shear strength of two-way flat concrete slabs without shear reinforcement.

Keywords: concrete; punching shear; two-way flat slabs; ANFIS

1. Introduction

Generally, the contact surfaces between columns and slabs are very small in flab slab systems, and therefore high stresses are concentrated in the connections area. A punching shear failure may occur if the stresses exceed the limitations. This failure is brittle and may occur unexpectedly. To avoid this type of failure, various construction methods have been developed [1].

In the design and analysis of two-way flat slabs without shear reinforcement, the punching shear strength is an important parameter. Much research has been conducted throughout the current century, and the key variables affecting the punching shear strength of slabs have been identified [2–5]. Most of the research has been concerned with the generation of experimental data and the development of empirical equations in addition to the equations proposed by ACI 318-14 [6], BS-8110-97 [7], Model Code 2010 [8], and Euro-Code 2 [9]. However, the subject still needs further study to understand the complexity of punching shear behavior and to develop better prediction tools.

Fuzzy logic (FL) and neural network (NN) techniques have been widely used in civil engineering applications over the last two decades. In this study, an alternative model was developed within the framework of an adaptive neuro-fuzzy interface system (ANFIS) to predict the punching shear of two-way slabs without shear reinforcement. This model was developed using a large database (207 experimental results) compiled from 17 scientific studies. The predictions from this model were compared to those from the equations proposed in commonly used codes.
2. ANFIS: Literature Review

The solution of problems associated with engineering systems requires the use of several different disciplines implementing different methods of modeling and analysis. For a complex engineering system, often a physics-based mathematical model is used, which is extremely difficult to formulate. For such a system, several other approaches (neural networks, fuzzy inference systems, etc.) under the rubric of “soft computing” provide a useful alternative. Soft computing models are becoming popular and have been of increasing interest during the last three decades. This approach is based on human reasoning and learning and uses the human tolerance for uncertainty and imprecision and fuzziness in the decision-making processes [10]. Recently, artificial neural networks (ANNs) and ANFIS have been used extensively for various civil engineering applications in construction management, building materials, hydraulics, structural engineering, geotechnical and transportation engineering, etc. Here, a selected few recent works in the area related to our subject are presented. Kasperkiewicz et al. [11] developed an ANN to predict the compressive strength of high-performance concrete mixes. Takagi and Sugeno [12] developed a fuzzy inference system (FIS) model and applied it to modeling and controlling concepts. Topçu and Saridemir [13] applied ANN and FL to predict rubberized mortar properties. Bilgehan [14] used ANFIS and NN models to determine the critical buckling load. Tesfamariam and Najjran [15] developed an ANFIS model to estimate the concrete strength of a given mix proportion based on existing datasets. Akbulut et al. [16] used ANFIS to predict the shear modulus and damping coefficient of sand and rubber mixtures. Inan et al. [17] used an adaptive neuro-fuzzy system to simulate nonlinear mapping in the sulphate expansion of Portland cement (PC) mortar. Experimental data that had previously been collected for various parameters were treated in the analysis. Fonseca et al. [18] developed a neuro-fuzzy model to classify and to predict the behavior of steel beams under concentrated loads. Wang and Elhag [19] applied ANFIS to assess bridge risk based on multiple bridge maintenance projects. Batenia and Jeng [20] used ANFIS to investigate the characteristics of a scour hole that develops around a group of piles in a well-defined field situation and to determine the parameters that control the scour hole. Mashrei [21] developed an ANFIS model to predict the shear strength of concrete beams reinforced with fiber-reinforced polymer (FRP) bars. Bilgehan and Kurtoglu [22] applied ANFIS to predict the moment capacities of reinforced concrete (RC) slabs exposed to fire. Mansouri et al. [23] investigated the ability of radial basis neural networks and ANFIS methods in the prediction of ultimate strength and strain of concrete cylinders confined with FRP sheets. Naderpour and Mirrashid [24] used ANFIS to determine the shear strength of RC beams with shear reinforcement. Basarir et al. [25] used an ANFIS model to predict the uniaxial compressive strength of cemented backfill.

3. Existing Equations Used for Two-Way Flat Slabs

For the design of a two-way flat slab–column connection, the shear stress is usually assumed to be a function of strength of concrete and the geometric parameters of the slab and column. The critical section for checking punching shear in slabs is usually situated between 0.5 and 2 times the effective depth from the edge of the load or reaction. Many empirical equations have been published to estimate the punching shear strength of two-way slabs, such as the equations proposed in ACI 318-14, BS-8110-97, Model-Code-2010, and Euro-Code 2 [6–9].

3.1. ACI 318-14 Building Code Equations

A set of simple equations were proposed in the ACI 318-14 code to calculate the shear strength provided by concrete. The control perimeter is half of the effective depth of the slab (0.5d) from the loaded area for punching shear stress. ACI 318-14 requires that the nominal shear resistance for slabs without shear reinforcement be approximated as the smallest value of \( V_n \) calculated from the following expressions:

\[
V_n = 0.083 \left( 2 + \frac{4}{\beta_c} \right) \lambda \sqrt{f'_c} b_0 d ,
\]  

(1)
\[ V_n = 0.083 \left( \alpha_s \frac{d}{b_o} + 2 \right) \lambda \sqrt{f'_c b_o d}, \quad (2) \]

\[ V_n = 0.33 \lambda \sqrt{f'_c b_o d}, \quad (3) \]

where \( V_n \) is the shear strength in N, \( b_o \) is the perimeter of the critical section in mm, \( d \) is the effective depth of slab in mm, and \( \lambda = 1.0 \) for normal weight concrete and 0.75 for all lightweight concrete. Otherwise, \( \lambda \) is determined based on volumetric proportions of lightweight and normal weight aggregates, but does not exceed 0.85. Here, \( \alpha_s = 40 \) for interior columns, 30 for edge columns, and 20 for corner columns; \( \beta_c \) is the ratio of the longer to the shorter dimension of the loaded area; and \( f'_c \) is the cylinder compressive strength of concrete in MPa.

### 3.2. Model Code 2010

The nominal punching shear strength is assumed to be proportional to \((f_{ck})^{1/3}\) in Model Code 2010. The influences of the slab depth and steel reinforcement are also considered in this model. The punching strength according to Model Code 2010 is expressed by

\[ V_n = 0.18 b_o d \times \xi \times \sqrt{\frac{100}{\rho} \times f_{ck}}, \quad (4) \]

where \( f_{ck} \) is the characteristic cylinder compressive strength in MPa, \( \xi = 1 + \frac{200}{d}^{1/2} \) is a size effect coefficient, \( d \) is the slab effective depth in mm, \( \rho \) is the ratio of flexure reinforcement, and \( b_o \) is the length of the control perimeter at 2\( d \) from the column face in mm.

### 3.3. British Code: BS-8110-97

The British Code provisions proposed the following expression to estimate the shear strength of slabs:

\[ V_n = 0.79 \frac{(100 \times \rho)^{1/3}}{25} \times \left( \frac{f_{cu}}{1.25} \right)^{1/3} b_o d, \quad (5) \]

where \( f_{cu} \) is the cubic compressive strength in MPa. It should be noted that in the British Code, the critical section for shear is considered to be 1.5\( d \) from the face of the column. All terms were defined previously.

### 3.4. Euro-Code 2 (EC2)

The Euro-Code 2 (EC2) recommends that the punching shear resistance be expressed as proportional to \((f_{ck})^{1/3}\), where \( f_{ck} \) is the compressive strength of concrete. In EC2, the influences of slab depth and steel reinforcement are also considered. The punching shear resistance according to EC2 may be calculated as

\[ V_n = \frac{0.18}{\gamma_c} K b_o d (1000 \times \rho \times f_{ck})^{1/3} \left( \frac{2d}{a_{crit}} \right) \geq 0.035 k^2 f_{ck}^{1/2} \left( \frac{2d}{a_{crit}} \right) b_o d, \quad (6) \]

where \( \gamma_c \) is the material resistance factor for concrete = 1.5, \( d \) is the effective depth, \( K = 1 + \sqrt{200/d} \leq 2 \) is the size factor of the effective depth, \( \rho \) is the flexural reinforcement ratio \( \leq 2\% \), \( f_{ck} \) is the cylinder compressive strength of concrete, and \( a_{crit} \) is the distance from column face to the control perimeter.

It should be noted that some codes do not consider the size effect in estimates of the punching shear strength of slabs, such as ACI 318-14, while some common codes, such as Model-Code-2010 and Euro-Code 2, consider the size effect in the design of slabs for punching shear in the same form as presented in Equations (4) and (6). Different forms of the size effect have been presented by many researchers to consider the effect of this factor on punching shear strength: More details about the size effect can be found in References [26–30].
4. ANFIS: An Introduction

Recently, a fundamental change has occurred in the methodology of empirical analysis. Because of the nonlinearity and high degree of uncertainty associated with structural behavior, traditional mathematical models are difficult to develop. As an alternative, FIS- and ANN-based models (belonging to “soft computing”) are being used for many civil engineering problems. Nowadays, ANNs have been accepted as very useful tools for modeling nonlinear systems and are being widely used. FIS has emerged as a useful tool to represent and analyze complex systems [31–33]. Each method has its own advantages and disadvantages. Whereas in FIS there is no systematic procedure for designing a fuzzy controller, ANNs have the ability to map the input and output datasets through supervised learning and a self-organized structure. For this reason, it was proposed to combine an FIS and ANN together to get ANFIS, which enhances the efficiency of the systems and the modeling of problems using available data. ANFIS is thus an integration of an ANN and an FIS and uses basic FIS rules and the ANN network architecture to update system parameters using existing input and output pairs. ANFIS was first introduced by Jang [34]. In both an ANN and FIS, input parameters pass through the input layer using an input membership function, and the output parameters are seen in the output layer using output membership functions. In this method, the parameters are changed until an optimal solution is reached using a learning algorithm. A basic flow diagram of computations in ANFIS is illustrated in Figure 1. Several fuzzy inference systems have been developed by different researchers [12,35–38], who commonly use Mamdani-type and Takagi–Sugeno-type systems. In this study, a Takagi–Sugeno-type system was used.

![Figure 1. The basic flow diagram for computations in an adaptive neuro-fuzzy interface system (ANFIS).](image)

5. ANFIS: This Study

In this study, an ANFIS model was developed using MATLAB R2013a [39] with five input parameters: The slab effective depth (d), compressive strength of concrete (f'_c), reinforcement ratio (ρ), yield strength of reinforcement (f_y), and width of square loaded area (c). The output variable is punching shear strength of a two-way slab (V). A set of 207 experimental data points, collected from several sources [40–56], was used to develop the model. The experimental data were randomly divided into two sets: The first one, with 164 data points, was used for training the model, and the
second one, with 43 data points, was used for testing. A subtractive clustering technique produced by Chiu [57] was used to generate the ANFIS model with the (genfis2) function in MATLAB. Genfis2 is used to help in the creation of the initial set of membership functions for sets of input and output data. Genfis2 preforms this model by extracting a set of rules. The rule extraction method first uses the subclust function to determine the number of rules and antecedent membership functions. The type and the number of membership functions were evaluated when the training and testing datasets were giving good predictions according to the root mean square error (RMSE). After experimenting with different learning algorithms with a number of different epochs, the best correlations were found through a hybrid learning algorithm (a combination of least squares and back-propagation algorithms for membership function parameter estimations). The final errors of the model for training and testing were 0.45 and 0.52, respectively, and were achieved after 200 epochs. The structure of the ANFIS model is illustrated in Figure 2. In the model, 10 of the Gaussian membership functions (gaussmf) are selected for each input, and 10 rules define the relationship between inputs and outputs. A Gaussian membership function has two parameters: \( c \), responsible for its center, and \( \sigma \), responsible for its width, and the equation for this type is [39,58]

\[
A(x)_{\text{Gauss}} = \exp \left(-\frac{(x-c)^2}{2\sigma}\right). \tag{7}
\]

Readers are referred to Reference [58] for more details on this type of membership function. The numerical range of input parameters of the current study is listed in Table 1. The data used to build the ANFIS model are summarized in Table A1 in Appendix A. After the training procedure, the model was tested using the remaining data not used for the training. Figure 3 shows the performance for training and testing datasets. Figures 4 and 5 show the matching of the experimental results with the results of the ANFIS model for both training and testing sets, respectively. Figure 6 shows a comparison between the experimental results of punching shear and the results predicted by the ANFIS model for all samples used in the model (training and testing sets). The adequacy of the developed ANFIS was evaluated by considering the coefficient of correlation (\( R \)), the average and standard deviation of the ratio of predicted to experimental punching shear strength, and the root mean square error (RMSE). The equations of the statistical parameter RMSE and the coefficient of correlation (\( R \)) that were used to compare the performance of each method are

\[
\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{N} (V_{ne} - V_{ni})^2}{N}}, \tag{8}
\]

\[
R = 1 - \sqrt{\frac{\sum_{i=1}^{N} (V_{ne} - V_{ni})^2}{\sum_{i=1}^{N} (V_{ne})^2}}, \tag{9}
\]

where \( V_{ne} \) and \( V_{ni} \) are the experimental and prediction nominal punching shear strength (\( V_n \)) of two-way flat slabs, respectively, and \( N \) is the total number of samples considered.

| Table 1. Range of input parameters in the database. |
|---------------------------------------------------|
| Parameters                                         | Range         |
|---------------------------------------------------|---------------|
| The slab effective depth (\( d \)) (mm)            | 35–550        |
| Concrete cylinder compressive strength (\( f'_c \)) (MPa) | 14.2–119      |
| Reinforcement ratio (\( \rho \)) (%)               | 0.25–5.01     |
| Yield strength of reinforcement (\( f_y \)) (MPa)   | 294–720       |
| Width of square loaded area (\( c \)) (mm)         | 80–500        |
The slab effective depth, yield strength of reinforcement, and the width of square loaded area are the experimental and prediction nominal punching shear strength parameters. The RMSE and the coefficient of determination were calculated to compare the performance of the ANFIS model for both training and testing sets. The adequacy of the model for training and testing were 0.45 and 0.52, respectively, and \( N \) is the total number of samples considered.

**Figure 2.** Network Structure of the ANFIS model.

**Figure 3.** Convergence of the ANFIS for training and testing sets.

**Figure 4.** Experimental and predicted punching shear strength (training dataset).
when comparing the correlation coefficient for all models for training, testing, and the combined datasets. The values of 0.996, 0.995, and 0.995 for the ANFIS training, testing, and combined datasets, respectively, were very close to 1.0 and higher than those of the other four design codes. Finally, the results of the five models was also made with the experimental results. It was noted that the results from BS-8110-97 were reasonable when compared to the experimental results. Table 2 summarizes the average and standard deviation (STDEV) of the ratios of predicted punching shear strength ($V_{nh}$) to the experimental results ($V_{ne}$). The ANFIS model gave an average $V_{nh}/V_{ne}$ ratio for the training and test datasets of 1.0 and 1.01, respectively, and a standard deviation of 0.11 and 0.13, respectively. These results indicate that the ANFIS model could make more reliable predictions of the punching shear strength compared to those from the four design codes. Table 3 also confirms this conclusion when comparing the correlation coefficient for all models for training, testing, and the combined datasets. The values of 0.996, 0.995, and 0.995 for the ANFIS training, testing, and combined datasets, respectively, were very close to 1.0 and higher than those of the other four design codes. Finally, the same conclusion could be made from the root mean square error, as listed in Table 3: The minimum values of the RMSE were 0.45 and 0.52 for the training and testing sets, respectively.

**Figure 5.** Experimental and predicted punching shear strength (testing dataset).

**Figure 6.** Experimental and predicted punching shear strength for all samples.

### 6. ANFIS: Results and Comparison

Figures 7–18 show the comparison of the results obtained from the ANFIS model, ACI-14 code, Model Code 2010, British Code, and Euro-Code 2 for both training and testing datasets. A comparison of the results of the five models was also made with the experimental results. It was noted that the results of the ANFIS model were better than the results of four design codes: However, the results from BS-8110-97 were reasonable when compared to the experimental results. Table 2 summarizes the average and standard deviation (STDEV) of the ratios of predicted punching shear strength ($V_{nh}$) to the experimental results ($V_{ne}$). The ANFIS model gave an average $V_{nh}/V_{ne}$ ratio for the training and test datasets of 1.0 and 1.01, respectively, and a standard deviation of 0.11 and 0.13, respectively. These results indicate that the ANFIS model could make more reliable predictions of the punching shear strength compared to those from the four design codes. Table 3 also confirms this conclusion when comparing the correlation coefficient for all models for training, testing, and the combined datasets. The values of 0.996, 0.995, and 0.995 for the ANFIS training, testing, and combined datasets, respectively, were very close to 1.0 and higher than those of the other four design codes. Finally, the same conclusion could be made from the root mean square error, as listed in Table 3: The minimum values of the RMSE were 0.45 and 0.52 for the training and testing sets, respectively.
Figure 7. Experimental and predicted punching shear strength (training dataset).

Figure 8. Experimental and predicted punching shear strength (testing dataset).

Figure 9. Experimental and predicted punching shear strength for all samples.
Figure 10. Experimental and predicted punching shear strength (training dataset).

Figure 11. Experimental and predicted punching shear strength (testing dataset).

Figure 12. Experimental and predicted punching shear strength for all samples.
Figure 13. Experimental and predicted punching shear strength (training dataset).

Figure 14. Experimental and predicted punching shear strength (testing dataset).

Figure 15. Experimental and predicted punching shear strength for all samples.
Figure 16. Experimental and predicted punching shear strength (training dataset).

Figure 17. Experimental and predicted punching shear strength (testing dataset).

Figure 18. Experimental and predicted punching shear strength for all samples.
Table 2. Comparison of punching shear between the experimental and predicted results for the training and testing sets. STDEV: Standard deviation.

| Specimens No. | Average of $V_{n}/V_{nc}$ | STDEV of $V_{n}/V_{nc}$ |
|---------------|-----------------------------|--------------------------|
|               | ANFIS | ACI-14 Code | Model-Code 2010 | BS-8110 Code | Euro-Code 2 | ANFIS | ACI-14 Code | Model-Code 2010 | BS-8110 Code | Euro-Code 2 |
| Training set  | 164   | 1.0         | 0.88             | 1.10         | 1.01        | 1.45     | 0.11     | 0.30         | 0.16         | 0.14        | 0.20        |
| Testing set   | 43    | 1.01        | 0.84             | 1.07         | 0.98        | 1.42     | 0.13     | 0.26         | 0.15         | 0.13        | 0.19        |

Table 3. Comparison summary of correlation (R) and root mean square error (RMSE %).

| Type                  | Correlation (R) | RSME % |
|-----------------------|-----------------|--------|
|                       | Training        | Testing| All Data | Training  | Testing |
| ANFIS                 | 0.996           | 0.995  | 0.995    | 0.45      | 0.52    |
| ACI 318-14 Code       | 0.927           | 0.952  | 0.927    | 2.06      | 2.05    |
| Model-Code-2010       | 0.986           | 0.992  | 0.986    | 0.93      | 0.72    |
| BS-8110-97            | 0.986           | 0.992  | 0.987    | 0.83      | 0.93    |
| Euro-Code 2           | 0.985           | 0.993  | 0.986    | 3.12      | 2.70    |

7. Parametric Studies

After building and testing the ANFIS, and based on the comparison between the results obtained from the ANFIS model and the ACI 318-14 code, Model Code 2010, BS-8110, and Euro-Code 2, it could be concluded that the ANFIS was a suitable model in the prediction of the punching shear strength of two-way flat concrete slabs. The effect of each input parameter used to build the model was further investigated. The methodology of the parametric study was to vary one input parameter at a time, and the other input parameter were kept constant. Figures 19–23 show the predicted punching shear strength of a two-way flab slab as a function of each input variable. They show that the punching shear strength increased with an increase in the slab effective depth, concrete strength, and width of square loaded area. In general, the parametric tendencies of ANFIS agreed with the results from the ACI318-14 code, Model Code 2010, BS-8110, and Euro-Code 2, as shown in Figures 19–21. The punching shear strength increased with an increase in the reinforcement ratio: This result agreed with the other models, except for the ACI code, as shown in Figure 22. Finally, the sensitivity of the punching shear strength to the yield strength of reinforcement is presented in Figure 23, where it can be seen that all models except ANFIS showed no effect on the punching shear strength. Interestingly, ANFIS predicted a slight increase in shear strength with increasing yield strength, which was in agreement with some of the experimental results used to build the ANFIS model.
Figure 19. Effect of slab effective depth on the punching shear strength.

Figure 20. Effect of concrete compressive strength on the punching shear strength.

Figure 21. Effect of width of square loaded area on the punching shear strength.

Figure 22. Effect of the reinforcement ratio on the punching shear strength.

Figure 23. Effect of yield strength of reinforcement on the punching shear strength.

Figure 24. Conclusions

An adaptive neuro-fuzzy inference system (ANFIS) was developed to predict the punching shear strength of two-way flat concrete slabs without shear reinforcement. A database of 207 test results available in the literature was used to train and test the model. The database covered a rather wide range of two-way flat slab parameters, including slab thickness, concrete strength, reinforcement ratio, yield strength of reinforcement, and width of square loaded area. Five variables were selected as inputs to the ANFIS, with punching shear strength as the output variable. Within the framework of ANFIS, different models may be developed using different learning algorithms with different membership functions and epochs. After experimenting with several of these different models, a model was chosen that had the best potential to predict experimental results. An ANFIS model with a hybrid learning algorithm, 200 epochs, and 10 Gaussian membership functions was selected and then tested. The results from the ANFIS model were compared to the experimental results and to those from the equations recommended in ACI 318-14, BS-8110-97, Model Code 2010, and Euro-Code 2. For these comparisons, the correlation coefficient (R), the root mean square error (RMSE), and the average and standard deviations of the ratios of predicted ($V_{ni}$) to experimental ($V_{ne}$) punching shear strength were used as evaluation criteria. The values of R, RMSE, and average and standard deviations of $V_{ni}/V_{ne}$ for the training set were found to be 0.996, 0.45, 1.0, and 0.11, respectively, and for the testing set were 0.995, 0.52, 1.1, and 0.13, respectively, for the ANFIS model. This demonstrated that (i) the ANFIS model was capable of making highly reliable predictions of experimental results, (ii) the ANFIS model outperformed the equations recommended in four design codes currently used in practice, and (iii) the ANFIS model showed that it was a good tool for...
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### Appendix A

#### Table A1. Experimental data used to construct the ANFIS.

| Test No. | $d$  | $f_c$ | $f_y$ | $\rho$ | $c$ | $V_u$ | Reference |
|----------|------|-------|-------|--------|-----|-------|-----------|
| 1        | 118  | 25.2  | 332   | 1.16   | 254 | 365   |           |
| 2        | 118  | 36.8  | 332   | 1.16   | 254 | 351   |           |
| 3        | 118  | 20.3  | 332   | 1.16   | 254 | 356   |           |
| 4        | 114  | 19.5  | 321   | 2.5    | 254 | 400   |           |
| 5        | 114  | 37.4  | 321   | 2.5    | 254 | 467   |           |
| 6        | 114  | 27.9  | 321   | 2.5    | 254 | 512   |           |
| 7        | 114  | 22.6  | 321   | 3.74   | 254 | 445   |           |
| 8        | 114  | 26.5  | 321   | 3.74   | 254 | 534   |           |
| 9        | 114  | 34.5  | 321   | 3.74   | 254 | 547   |           |
| 10       | 118  | 26.1  | 332   | 1.18   | 356 | 400   | [43]      |
| 11       | 114  | 25.3  | 321   | 3.74   | 356 | 498   |           |
| 12       | 121  | 26.2  | 294   | 0.55   | 356 | 236   |           |
| 13       | 114  | 14.2  | 324   | 0.48   | 254 | 178   |           |
| 14       | 114  | 47.6  | 321   | 0.48   | 254 | 200   |           |
| 15       | 114  | 43.9  | 341   | 2      | 254 | 505   |           |
| 16       | 114  | 50.5  | 325   | 3.02   | 254 | 578   |           |
| 17       | 118  | 29.3  | 332   | 1.16   | 254 | 356   |           |
| 18       | 114  | 27.8  | 321   | 2.5    | 356 | 534   |           |
| 19       | 114  | 47.7  | 303   | 1.01   | 254 | 334   |           |
| 20       | 114  | 27.5  | 400   | 1.38   | 305 | 394   |           |
| 21       | 114  | 23.2  | 400   | 1.06   | 254 | 390   |           |
| 22       | 114  | 22.3  | 400   | 1.03   | 254 | 356   |           |
| 23       | 114  | 23.8  | 400   | 1.13   | 254 | 334   |           |
| 24       | 114  | 25.3  | 400   | 1.02   | 254 | 379   |           |
| 25       | 114  | 33.1  | 400   | 1.13   | 254 | 374   |           |
| 26       | 114  | 20.4  | 400   | 1.13   | 254 | 312   | [44]      |
| 27       | 114  | 24.2  | 400   | 1.06   | 203 | 379   |           |
| 28       | 114  | 22.3  | 305   | 1.5    | 305 | 433   |           |
| 29       | 114  | 26.5  | 400   | 1.38   | 152 | 312   |           |
| 30       | 114  | 24.4  | 400   | 1.06   | 254 | 393   |           |
| 31       | 114  | 22.1  | 400   | 1.06   | 203 | 343   |           |
| 32       | 51   | 21.1  | 386   | 1.1    | 152 | 79    |           |
| 33       | 51   | 15.5  | 386   | 1.1    | 203 | 93    |           |
| 34       | 50   | 27.2  | 386   | 2.2    | 203 | 133   |           |
| 35       | 51   | 22.9  | 386   | 2.2    | 254 | 152   |           |
| 36       | 51   | 23.9  | 386   | 2.2    | 305 | 114   |           |
| 37       | 51   | 27.7  | 386   | 2.2    | 356 | 139   |           |
| 38       | 51   | 25.2  | 386   | 2.2    | 356 | 184   |           |
| 39       | 51   | 24.9  | 386   | 1.1    | 406 | 145   |           |
| 40       | 50   | 24.6  | 386   | 2.2    | 406 | 185   |           |
| 41       | 50   | 27.8  | 386   | 1.1    | 152 | 102   |           |
| 42       | 50   | 28.5  | 386   | 1.1    | 102 | 86    |           |
| 43       | 50   | 24.9  | 386   | 2.2    | 102 | 102   |           |
| 44       | 50   | 53.8  | 386   | 2.2    | 152 | 172   |           |
| 45       | 50   | 21.1  | 386   | 1.1    | 152 | 99    |           |
| 46       | 50   | 17.2  | 386   | 2.2    | 152 | 105   |           |
| 47       | 51   | 18.3  | 336   | 2.2    | 152 | 99    |           |
| 48       | 51   | 23.3  | 336   | 1.1    | 254 | 109   |           |
| 49       | 50   | 26.4  | 386   | 2.2    | 305 | 159   |           |
| 50       | 50   | 20.0  | 386   | 1.1    | 152 | 112   |           |
| Test No. | $d$ | $f_c$ | $f_y$ | $\rho$ | $e$ | $V_n$ | Reference |
|---------|-----|-------|-------|-------|-----|-------|-----------|
| 51      | 100 | 35.7  | 706   | 0.8   | 125 | 216   | [42]      |
| 52      | 99  | 28.6  | 701   | 0.81  | 125 | 194   |           |
| 53      | 199 | 28.6  | 670   | 0.89  | 250 | 600   |           |
| 54      | 200 | 30.3  | 657   | 0.8   | 250 | 603   |           |
| 55      | 98  | 33.3  | 720   | 0.35  | 125 | 145   |           |
| 56      | 99  | 31.4  | 712   | 0.34  | 125 | 148   |           |
| 57      | 200 | 31.7  | 668   | 0.34  | 250 | 489   |           |
| 58      | 197 | 30.2  | 664   | 0.35  | 250 | 444   |           |
| 59      | 77  | 23.3  | 500   | 1.2   | 200 | 176   |           |
| 60      | 77  | 33.4  | 500   | 0.92  | 200 | 194   |           |
| 61      | 79  | 21.7  | 480   | 0.75  | 200 | 165   |           |
| 62      | 79  | 31.2  | 480   | 0.8   | 200 | 186   |           |
| 63      | 200 | 36.3  | 530   | 0.98  | 250 | 825   |           |
| 64      | 128 | 34.5  | 485   | 0.98  | 160 | 390   |           |
| 65      | 64  | 34.5  | 480   | 0.98  | 80  | 117   |           |
| 66      | 128 | 35.7  | 485   | 0.98  | 160 | 365   |           |
| 67      | 64  | 35.7  | 480   | 0.98  | 80  | 105   |           |
| 68      | 64  | 37.8  | 480   | 0.98  | 80  | 105   |           |
| 69      | 41  | 31.5  | 530   | 0.42  | 100 | 36    |           |
| 70      | 41  | 31.5  | 530   | 0.69  | 100 | 49    |           |
| 71      | 41  | 36.2  | 530   | 0.82  | 100 | 56    |           |
| 72      | 41  | 36.2  | 530   | 1.03  | 100 | 66    |           |
| 73      | 41  | 30.4  | 530   | 1.16  | 100 | 71    |           |
| 74      | 41  | 30.4  | 530   | 1.29  | 100 | 71    |           |
| 75      | 41  | 30.4  | 530   | 1.45  | 100 | 79    |           |
| 76      | 41  | 30.6  | 530   | 0.52  | 100 | 44    |           |
| 77      | 41  | 30.6  | 530   | 0.8   | 100 | 55    |           |
| 78      | 41  | 35.3  | 530   | 0.8   | 100 | 49    |           |
| 79      | 41  | 35.3  | 530   | 0.69  | 100 | 52    |           |
| 80      | 41  | 35.3  | 530   | 1.99  | 100 | 85    |           |
| 81      | 47  | 29.4  | 530   | 0.44  | 100 | 45    |           |
| 82      | 47  | 29.4  | 530   | 0.69  | 100 | 66    |           |
| 83      | 47  | 31.7  | 530   | 1.99  | 100 | 97    |           |
| 84      | 35  | 39.6  | 530   | 0.42  | 100 | 29    |           |
| 85      | 35  | 39.6  | 530   | 0.69  | 100 | 38    |           |
| 86      | 35  | 31.7  | 530   | 1.99  | 100 | 73    |           |
| 87      | 54  | 28.3  | 530   | 0.42  | 100 | 63    |           |
| 88      | 54  | 33.5  | 530   | 0.69  | 100 | 88    |           |
| 89      | 41  | 31.5  | 530   | 0.56  | 100 | 49    |           |
| 90      | 41  | 36.2  | 530   | 0.88  | 100 | 57    |           |
| 91      | 41  | 30.6  | 530   | 1.11  | 100 | 67    |           |
| 92      | 47  | 29.4  | 530   | 1.29  | 100 | 90    |           |
| 93      | 35  | 39.6  | 530   | 1.29  | 100 | 57    |           |
| 94      | 54  | 33.5  | 530   | 1.29  | 100 | 124   |           |
| 95      | 54  | 28.3  | 530   | 1.99  | 100 | 126   |           |
Table A1. Cont.

| Test No. | $d$ | $f_c$ | $f_y$ | $\rho$ | $e$ | $V_n$ | Reference |
|---------|-----|------|------|------|----|------|-----------|
| 96      | 76  | 24.1 | 430  | 2.05 | 102| 129  | [47]      |
| 97      | 76  | 22.6 | 430  | 2.05 | 102| 136  |           |
| 98      | 113 | 22.6 | 430  | 2.14 | 152| 311  |           |
| 99      | 113 | 24.8 | 430  | 2.14 | 203| 357  |           |
| 100     | 122 | 24.8 | 430  | 0.66 | 203| 271  |           |
| 101     | 73  | 25   | 430  | 5.01 | 152| 202  |           |
| 102     | 86  | 23.2 | 430  | 0.45 | 152| 107  |           |
| 103     | 81  | 25.5 | 430  | 1.47 | 102| 121  |           |
| 104     | 123 | 22.1 | 430  | 0.47 | 203| 271  |           |
| 105     | 113 | 15.1 | 430  | 2.14 | 203| 278  |           |
| 106     | 81  | 14.5 | 430  | 1.47 | 152| 108  |           |
| 107     | 73  | 52.1 | 430  | 5.01 | 203| 323  |           |
| 108     | 81  | 52.1 | 430  | 1.47 | 152| 243  |           |
| 109     | 76  | 24.6 | 430  | 2.05 | 102| 129  |           |
| 110     | 81  | 25   | 430  | 1.47 | 152| 160  |           |
| 111     | 122 | 16.1 | 430  | 0.66 | 203| 230  |           |
| 112     | 122 | 52.1 | 430  | 0.66 | 203| 306  |           |
| 113     | 86  | 52.1 | 430  | 0.45 | 152| 148  |           |
| 114     | 95  | 42   | 490  | 1.47 | 150| 320  |           |
| 115     | 95  | 67   | 490  | 0.49 | 150| 178  |           |
| 116     | 95  | 70   | 490  | 0.84 | 150| 249  |           |
| 117     | 95  | 69   | 490  | 1.47 | 150| 356  |           |
| 118     | 90  | 66   | 490  | 2.37 | 150| 418  |           |
| 119     | 120 | 30   | 490  | 0.94 | 150| 396  |           |
| 120     | 125 | 68   | 490  | 0.64 | 150| 365  |           |
| 121     | 120 | 69   | 490  | 1.11 | 150| 436  |           |
| 122     | 120 | 74   | 490  | 1.61 | 150| 543  |           |
| 123     | 120 | 80   | 490  | 2.33 | 150| 645  |           |
| 124     | 70  | 75   | 490  | 1.52 | 150| 258  |           |
| 125     | 70  | 68   | 490  | 1.87 | 150| 267  |           |
| 126     | 95  | 72   | 490  | 1.47 | 220| 498  |           |
| 127     | 95  | 74   | 490  | 1.19 | 150| 356  |           |
| 128     | 120 | 70   | 490  | 0.94 | 150| 489  |           |
| 129     | 70  | 70   | 490  | 0.95 | 150| 196  |           |
| 130     | 95  | 71   | 490  | 1.47 | 300| 560  |           |
| 131     | 275 | 64   | 500  | 1.49 | 200| 2050 |           |
| 132     | 275 | 112  | 500  | 1.49 | 200| 2450 |           |
| 133     | 275 | 90   | 500  | 2.55 | 200| 2400 |           |
| 134     | 200 | 88   | 500  | 1.75 | 150| 1100 |           |
| 135     | 200 | 87   | 500  | 1.75 | 150| 1300 |           |
| 136     | 200 | 119  | 500  | 1.75 | 150| 1400 |           |
| 137     | 275 | 84   | 500  | 1.49 | 200| 2250 |           |
| 138     | 200 | 70   | 500  | 1.75 | 150| 1200 |           |
| 139     | 200 | 90   | 500  | 2.62 | 150| 1450 |           |
| 140     | 200 | 98   | 500  | 2.62 | 150| 1450 |           |
| 141     | 200 | 80   | 500  | 2.62 | 150| 1250 |           |
| 142     | 200 | 108  | 500  | 2.62 | 150| 1550 |           |
| 143     | 88  | 85   | 500  | 1.4  | 100| 330  |           |
| 144     | 200 | 90   | 643  | 0.8  | 250| 965  |           |
| 145     | 200 | 91   | 627  | 0.8  | 250| 1021 |           |
| 146     | 200 | 92   | 596  | 1.19 | 250| 1041 |           |
| 147     | 201 | 109  | 633  | 0.6  | 250| 960  |           |
| 148     | 202 | 84   | 634  | 0.33 | 250| 565  |           |
| 149     | 194 | 86   | 620  | 0.82 | 250| 889  |           |
| 150     | 198 | 95   | 631  | 0.8  | 250| 944  |           |
| Test No. | d   | $f_c$ | $f_y$ | $\rho$ | $\varepsilon$ | $V_u$ | Reference |
|---------|-----|-------|-------|------|------------|------|-----------|
| 151     | 98  | 88.2  | 550   | 0.58 | 150        | 224  | [49]     |
| 152     | 98  | 56.2  | 550   | 0.58 | 150        | 212  |          |
| 153     | 98  | 26.9  | 550   | 0.58 | 150        | 169  |          |
| 154     | 98  | 101.8 | 550   | 0.58 | 150        | 233  |          |
| 155     | 98  | 60.4  | 550   | 1.28 | 150        | 319  |          |
| 156     | 98  | 43.4  | 550   | 1.28 | 150        | 297  |          |
| 157     | 98  | 98.4  | 550   | 1.28 | 150        | 362  |          |
| 158     | 98  | 41.9  | 650   | 1.28 | 150        | 286  |          |
| 159     | 98  | 84.2  | 650   | 1.28 | 150        | 405  |          |
| 160     | 100 | 56.4  | 650   | 0.87 | 150        | 341  |          |
| 161     | 100 | 37.6  | 650   | 1.27 | 150        | 294  |          |
| 162     | 98  | 58.7  | 550   | 0.58 | 150        | 233  |          |
| 163     | 98  | 60.8  | 550   | 1.28 | 150        | 341  |          |
| 164     | 100 | 32.9  | 650   | 1.27 | 150        | 244  |          |
| 165     | 102 | 33.7  | 650   | 1.03 | 150        | 227  |          |
| 166     | 100 | 39.4  | 488   | 0.97 | 200        | 330  |          |
| 167     | 150 | 39.4  | 465   | 0.9  | 200        | 583  |          |
| 168     | 200 | 39.4  | 465   | 0.83 | 200        | 904  |          |
| 169     | 300 | 39.4  | 468   | 0.76 | 200        | 1381 |          |
| 170     | 400 | 39.4  | 433   | 0.76 | 300        | 2224 |          |
| 171     | 500 | 39.4  | 433   | 0.76 | 300        | 2681 |          |
| 172     | 210 | 27.6  | 400   | 1.5  | 260        | 1024 |          |
| 173     | 210 | 28.5  | 400   | 0.25 | 260        | 445  |          |
| 174     | 464 | 32.4  | 400   | 0.33 | 520        | 2153 |          |
| 175     | 210 | 32.2  | 400   | 0.25 | 260        | 408  |          |
| 176     | 210 | 29.3  | 400   | 0.33 | 260        | 550  |          |
| 177     | 96  | 34.7  | 400   | 1.5  | 130        | 236  |          |
| 178     | 100 | 34.7  | 400   | 0.75 | 130        | 243  |          |
| 179     | 102 | 34.7  | 400   | 0.25 | 130        | 118  |          |
| 180     | 210 | 40.5  | 400   | 0.25 | 260        | 439  |          |
| 181     | 102 | 34.7  | 400   | 0.33 | 130        | 141  |          |
| 182     | 210 | 28.5  | 400   | 0.33 | 260        | 540  |          |
| 183     | 100 | 24    | 718   | 0.8  | 250        | 270  |          |
| 184     | 100 | 24.4  | 718   | 0.8  | 250        | 250  |          |
| 185     | 125 | 27.2  | 718   | 0.64 | 150        | 265  |          |
| 186     | 124 | 33.1  | 488   | 1.54 | 250        | 483  |          |
| 187     | 190 | 33.5  | 531   | 1.3  | 300        | 825  |          |
| 188     | 260 | 31    | 524   | 1.1  | 350        | 1046 |          |
| 189     | 158 | 35    | 490   | 2.17 | 250        | 678  |          |
| 190     | 128 | 70    | 490   | 2.68 | 250        | 801  |          |
| 191     | 158 | 66.7  | 490   | 1.67 | 250        | 802  |          |
| 192     | 113 | 70    | 490   | 1.88 | 250        | 480  |          |
| 193     | 163 | 33    | 490   | 0.52 | 250        | 479  |          |
| 194     | 138 | 68.5  | 490   | 2.48 | 250        | 788  |          |
| 195     | 158 | 61.2  | 490   | 1.13 | 250        | 811  |          |
| 196     | 105 | 34    | 490   | 0.4  | 250        | 228  |          |
| 197     | 105 | 44.7  | 400   | 0.45 | 250        | 219  |          |
| 198     | 183 | 35    | 400   | 0.35 | 250        | 438  |          |
| 199     | 183 | 70    | 400   | 0.35 | 250        | 574  |          |
| 200     | 218 | 40    | 400   | 0.73 | 250        | 882  |          |
| 201     | 220 | 76    | 400   | 0.43 | 250        | 886  |          |
| 202     | 268 | 75    | 400   | 1.13 | 400        | 1721 |          |
| 203     | 263 | 65    | 400   | 1.44 | 400        | 2090 |          |
| 204     | 313 | 40    | 400   | 1.57 | 400        | 2234 |          |
| 205     | 313 | 60    | 400   | 1.57 | 400        | 2513 |          |
| 206     | 153 | 50.2  | 400   | 0.55 | 250        | 491  |          |
| 207     | 218 | 64.7  | 400   | 0.73 | 250        | 1023 |          |
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