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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 Najjaran [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 (0.5*d*) 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:

$$V_n = 0.083\left(2 + \frac{4}{\beta_c}\right)\lambda \sqrt{f_c'}\, b_o\, d\,, \tag{1}$$

$$V_n = 0.083\left(\alpha_s \frac{d}{b_o} + 2\right)\lambda\,\sqrt{f_c'}\,b_o\,d\,, \quad (2)$$

$$V_n = 0.33\,\lambda\,\sqrt{f_c'}\,b_o\,d\,, \quad (3)$$

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 λ = 1.0 for normal weight concrete and 0.75 for all lightweight concrete. Otherwise, λ is determined based on volumetric proportions of lightweight and normal weight aggregates, but does not exceed 0.85. Here, α_s = 40 for interior columns, 30 for edge columns, and 20 for corner columns; β_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

$$V_n = 0.18\,b_o\,d \times \xi \times \sqrt[3]{100 \times \rho \times f_{ck}}\,, \quad (4)$$

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

$$V_n = 0.79(100 \times \rho)^{\frac{1}{3}}\,(400/d)^{\frac{1}{4}} \times \left(\frac{f_{cu}}{25}\right)^{\frac{1}{3}}\,\frac{b_o d}{1.25}, \quad (5)$$

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 1.5d 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 $(f_{ck})^{\frac{1}{3}}$, 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

$$V_n = \frac{0.18}{\gamma_c} K b_o d (1000 \times \rho \times f_{ck})^{\frac{1}{3}}\,\frac{2d}{a_{crt}} \geq 0.035\,k^{\frac{3}{2}} f_{ck}{}^{\frac{1}{2}}\,\frac{2d}{a_{crt}}\,b_o d, \quad (6)$$

where γ_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, ρ is the flexural reinforcement ratio $\leq 2\%$, f_{ck} is the cylinder compressive strength of concrete, and a_{crt} 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). Deferent 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.

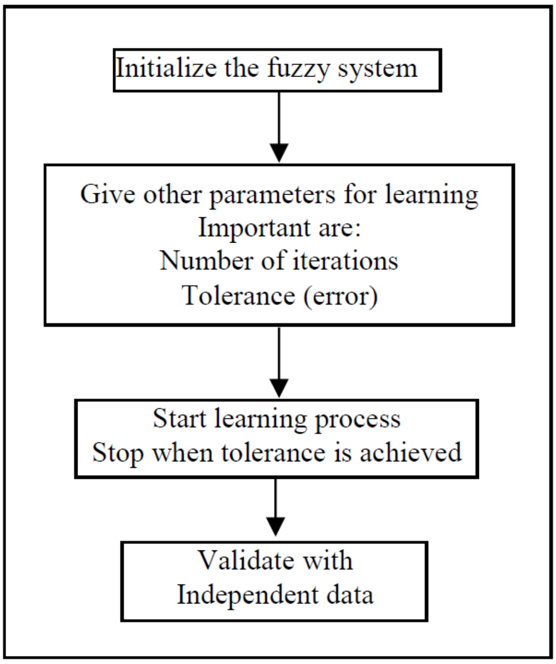

Figure 1. The basic flow diagram for computations in an adaptive neuro-fuzzy interface system (ANFIS).

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 σ, responsible for its width, and the equation for this type is [39,58]

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

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

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

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

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 (ρ) (%)	0.25–5.01
Yield strength of reinforcement (f_y) (MPa)	294–720
Width of square loaded area (c) (mm)	80–500

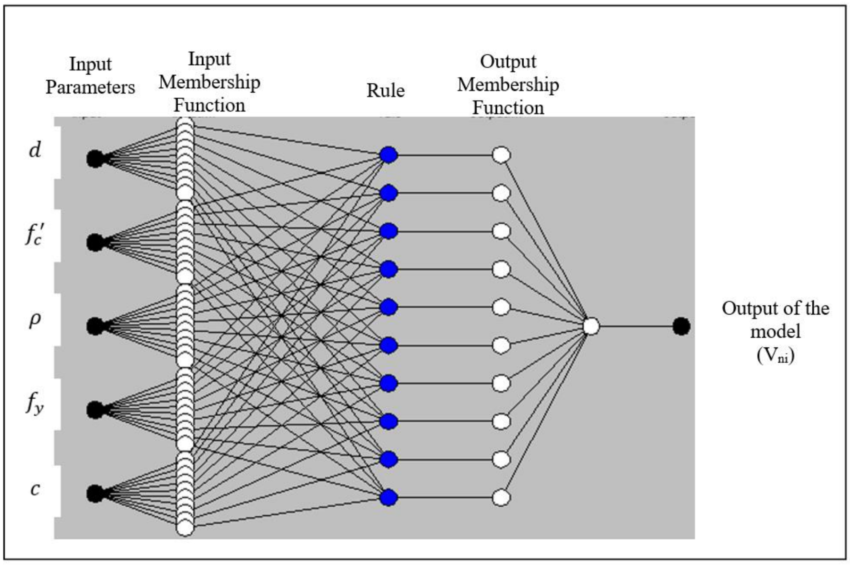

Figure 2. Network Structure of the ANFIS model.

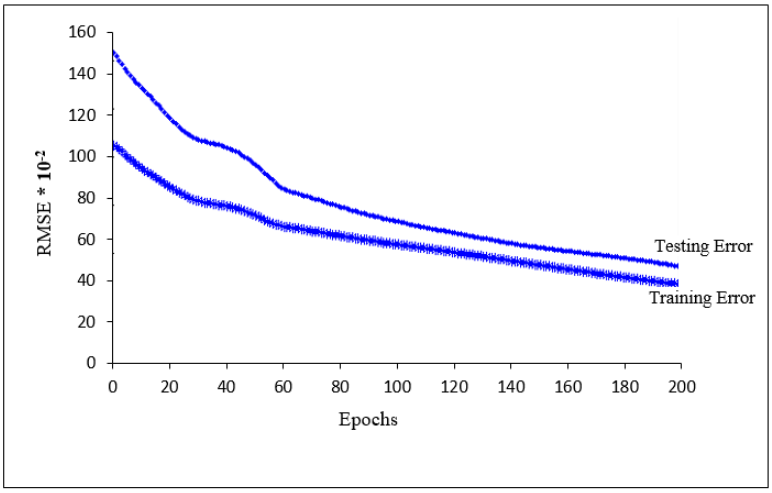

Figure 3. Convergence of the ANFIS for training and testing sets.

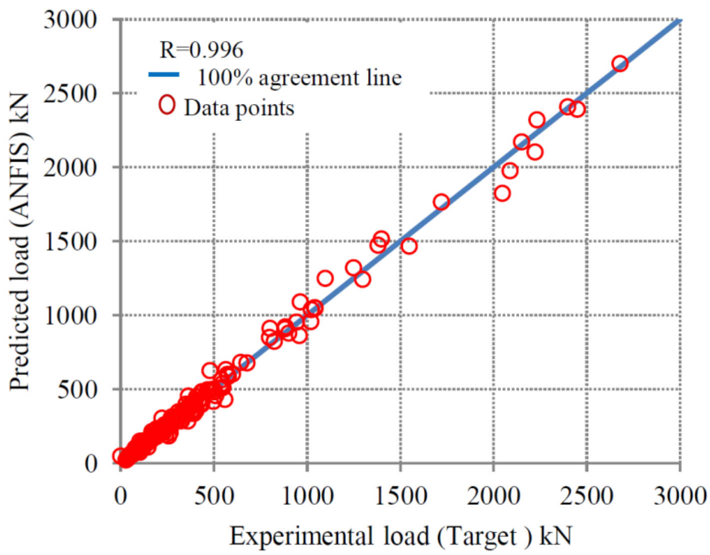

Figure 4. Experimental and predicted punching shear strength (training dataset).

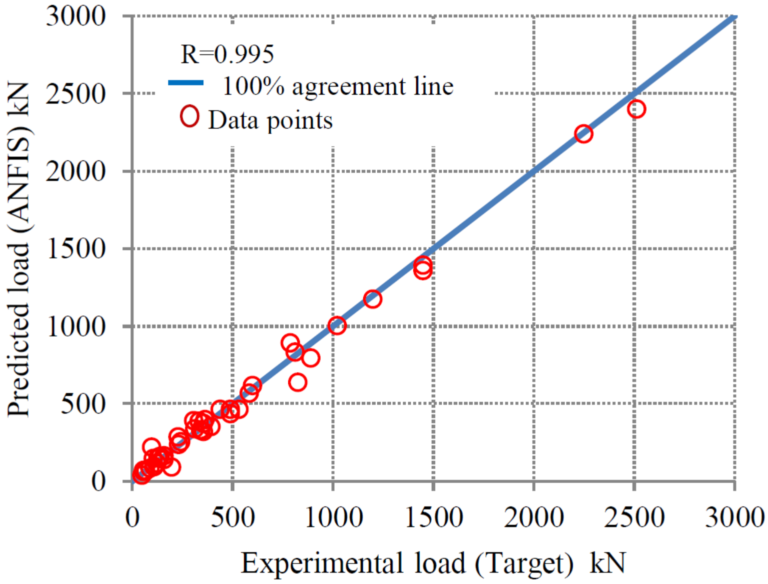

Figure 5. Experimental and predicted punching shear strength (testing dataset).

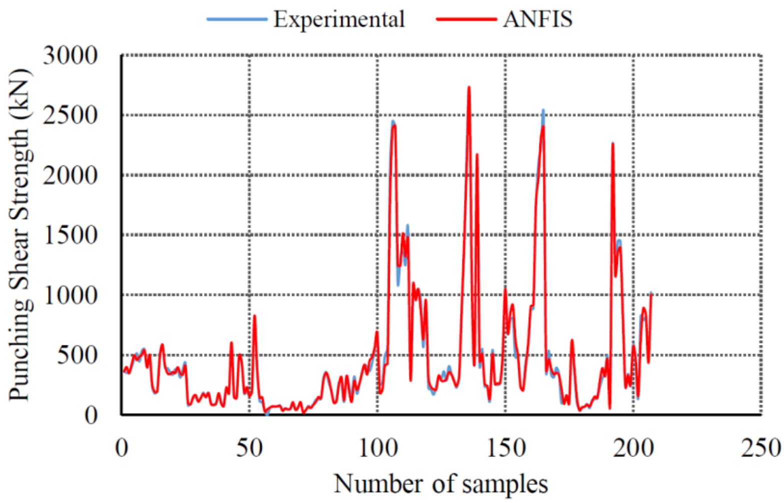

Figure 6. Experimental and predicted punching shear strength for all samples.

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_{ni}) to the experimental results (V_{ne}). The ANFIS model gave an average V_{ni}/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.

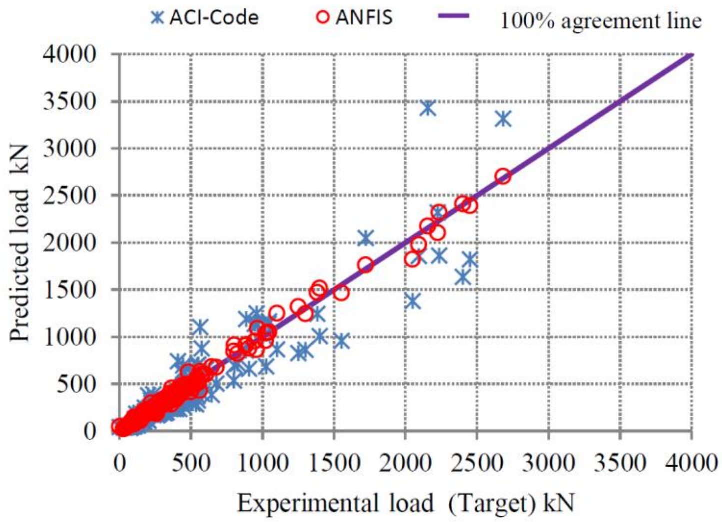

Figure 7. Experimental and predicted punching shear strength (training dataset).

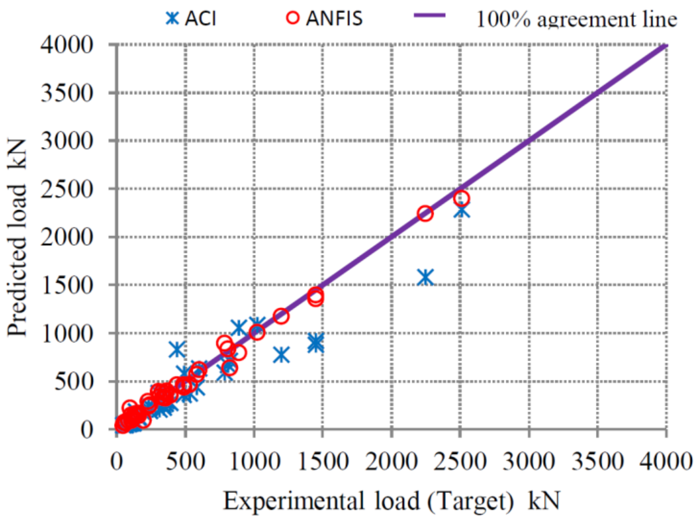

Figure 8. Experimental and predicted punching shear strength (testing dataset).

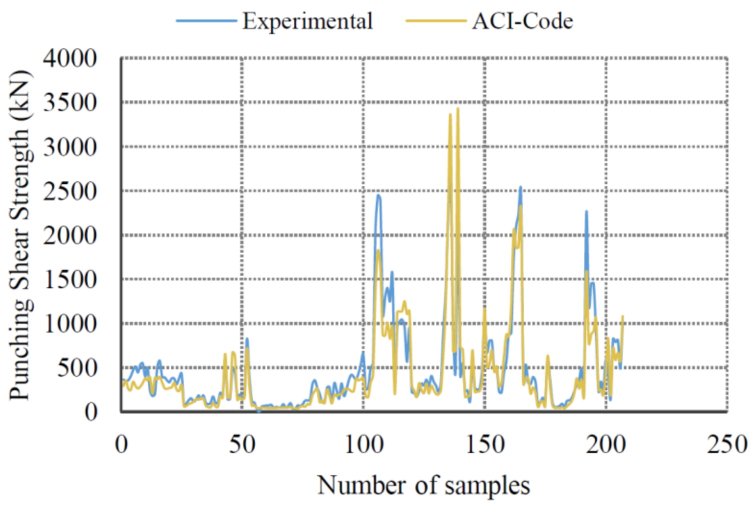

Figure 9. Experimental and predicted punching shear strength for all samples.

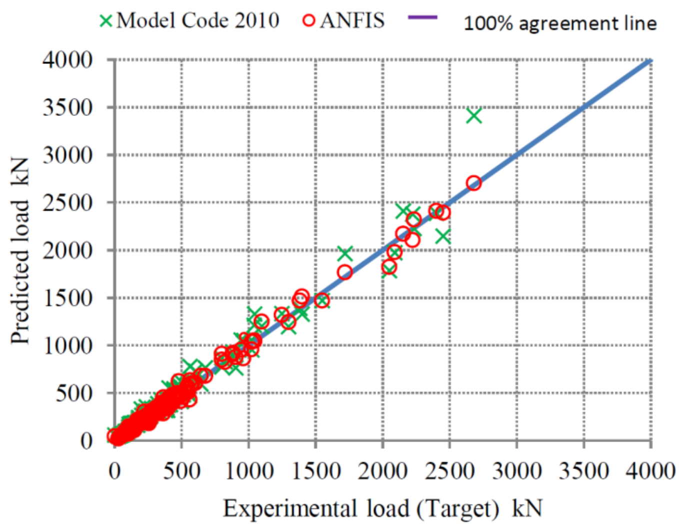

Figure 10. Experimental and predicted punching shear strength (training dataset).

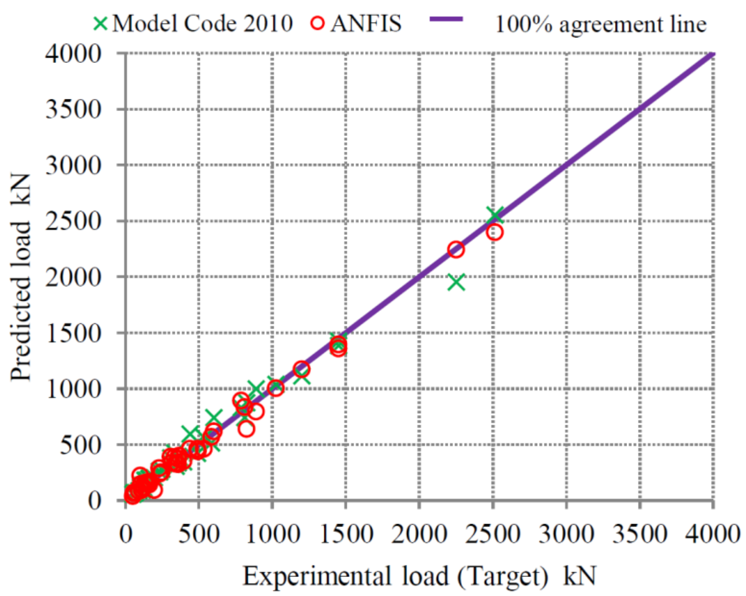

Figure 11. Experimental and predicted punching shear strength (testing dataset).

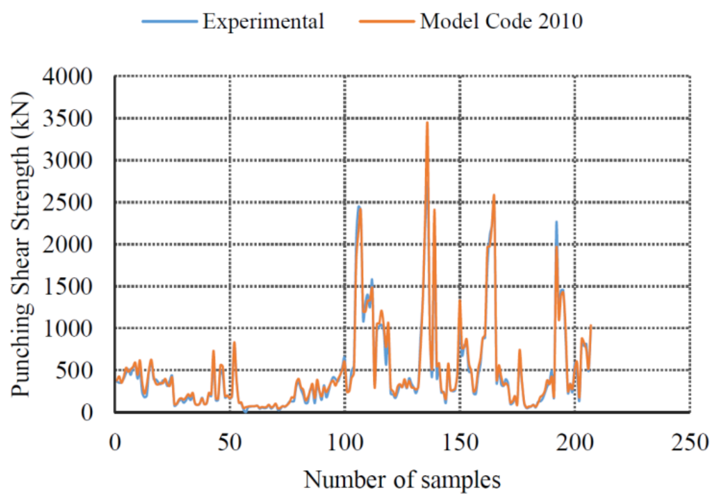

Figure 12. Experimental and predicted punching shear strength for all samples.

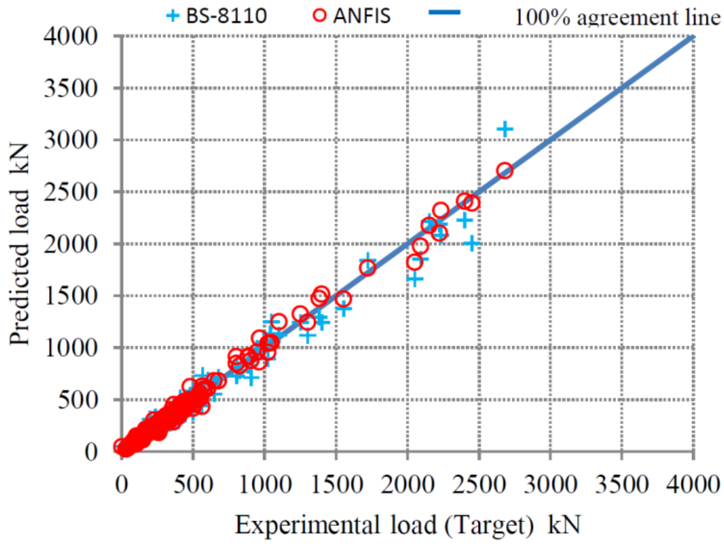

Figure 13. Experimental and predicted punching shear strength (training dataset).

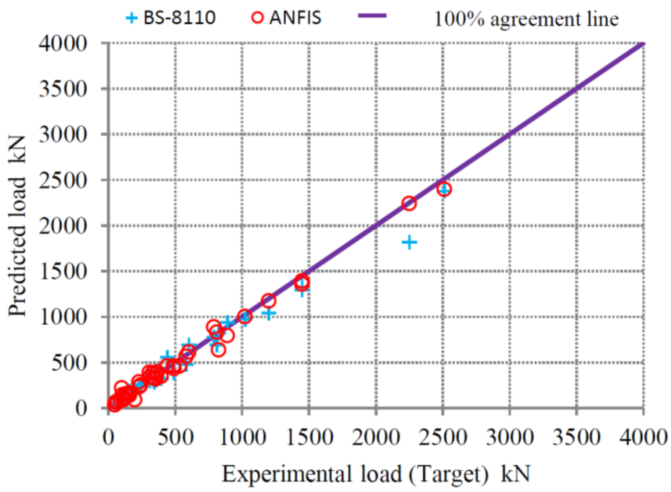

Figure 14. Experimental and predicted punching shear strength (testing dataset).

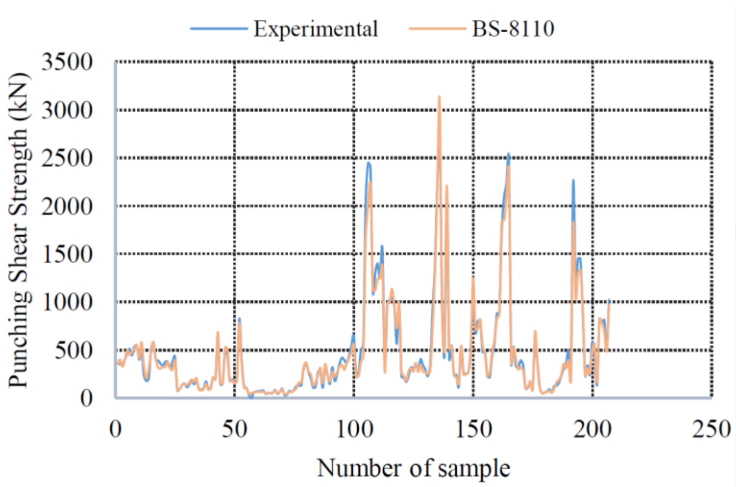

Figure 15. Experimental and predicted punching shear strength for all samples.

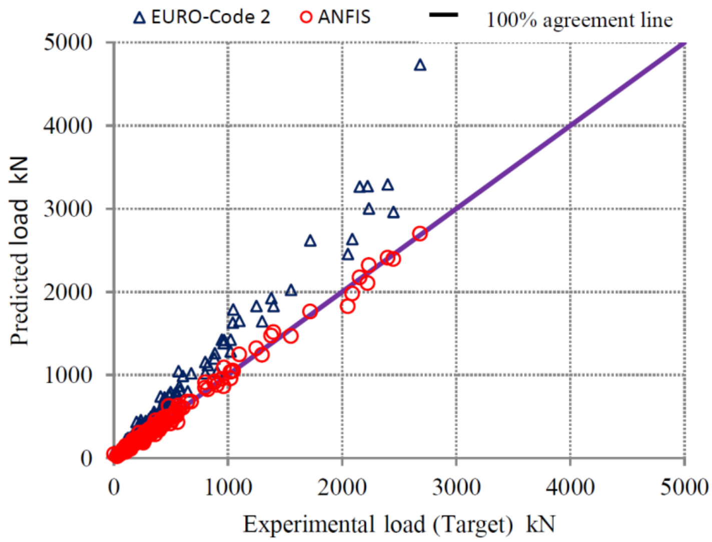

Figure 16. Experimental and predicted punching shear strength (training dataset).

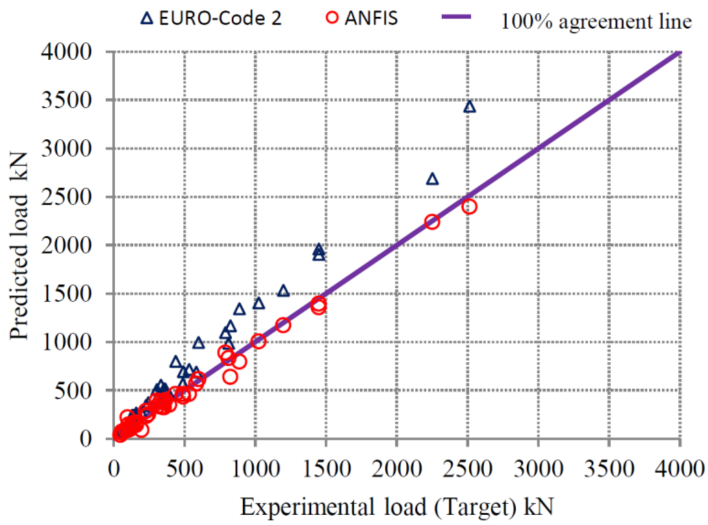

Figure 17. Experimental and predicted punching shear strength (testing dataset).

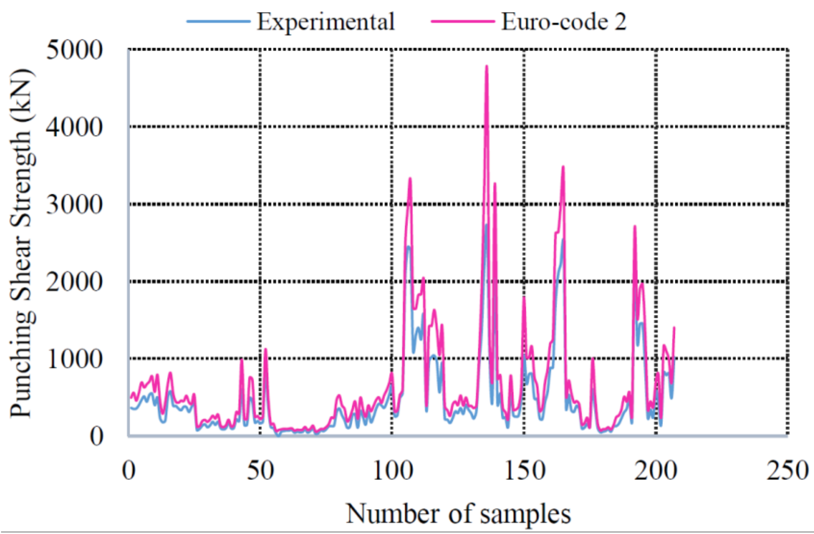

Figure 18. Experimental and predicted punching shear strength for all samples.

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_{ni}/V_{ne}					STDEV of V_{ni}/V_{ne}				
		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.

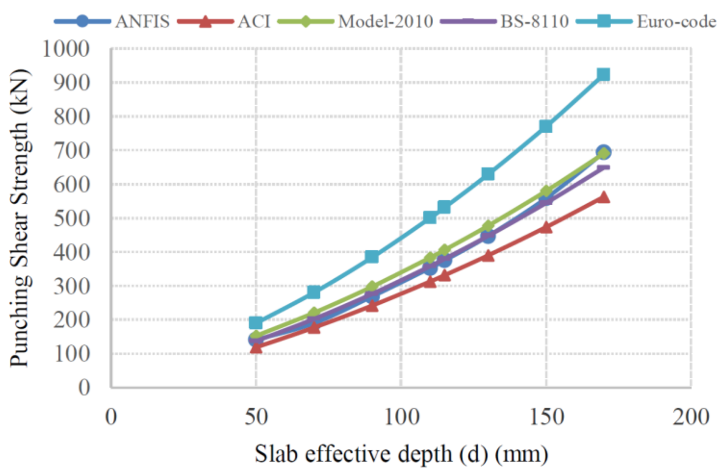

Figure 19. Effect of slab effective depth on the punching shear strength.

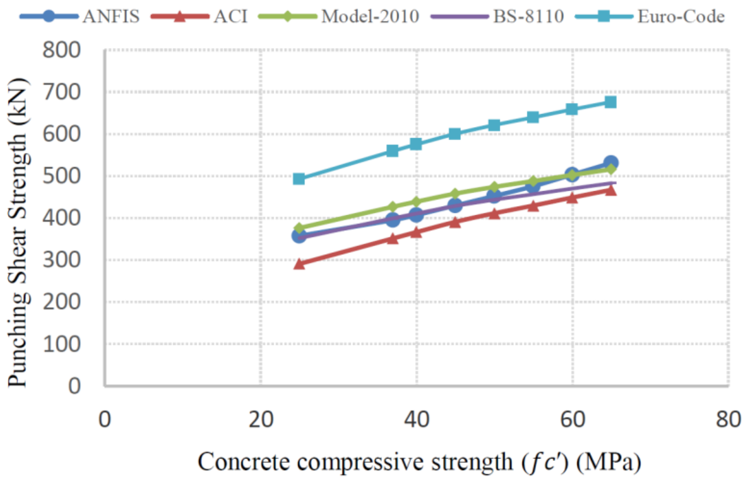

Figure 20. Effect of concrete compressive strength on the punching shear strength.

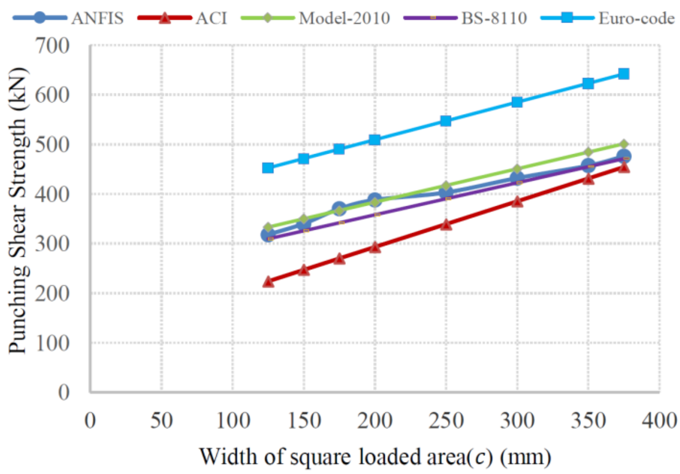

Figure 21. Effect of width of square loaded area on the punching shear strength.

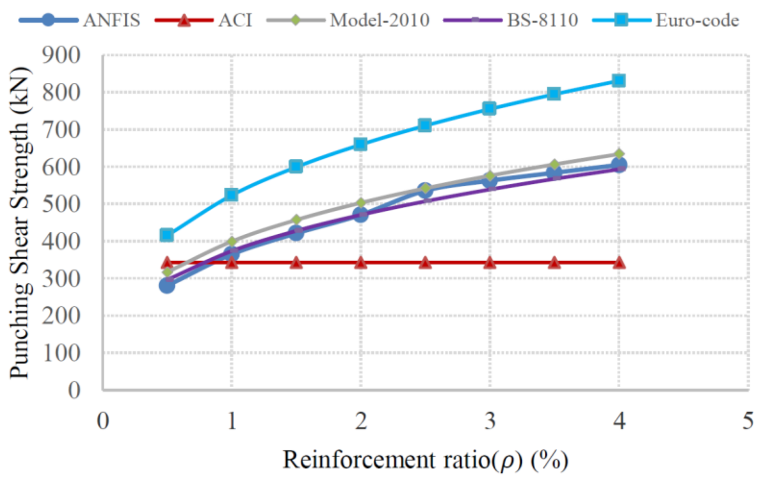

Figure 22. Effect of the reinforcement ratio on the punching shear strength.

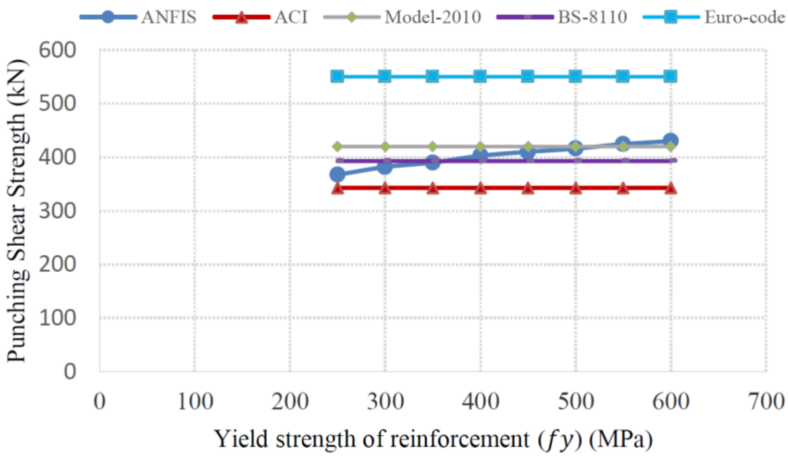

Figure 23. Effect of yield strength of reinforcement on the punching shear strength.

8. Conclusions

An adaptive neuro-fuzzy inference system (ANFIS)-based model 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 into 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 Vn_i/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 developing parametric studies to assess the influence of each parameter on the shear strength. In summary, the model developed in this study may serve as an economical, efficient, and reliable tool for the prediction of punching shear strength of flat concrete slabs.

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Appendix A

Table A1. Experimental data used to construct the ANFIS.

Test No.	d	fc	f_y	ρ	c	V_n	Reference
1	118	25.2	332	1.16	254	365	[43]
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	
11	114	25	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	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	[44]
21	114	23.2	400	1.06	254	390	
22	114	22	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	35.1	400	1.13	254	374	
26	114	20.4	400	1.13	254	312	
27	114	24.2	400	1.06	203	379	
28	114	23	400	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	[41]
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	386	1.1	305	114	
37	51	27.7	386	1.1	356	139	
38	51	25	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	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	386	2.2	152	105	
47	51	18	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	386	1.1	152	112	

Table A1. *Cont.*

Test No.	d	fc	f_y	ρ	c	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	[45]
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	[46]
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	0.6	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	fc	f_y	ρ	c	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	[40]
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	[48]
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	[50]
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	

Table A1. *Cont.*

Test No.	d	fc	f_y	ρ	c	V_n	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	[51]
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	[52]
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	[53]
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	[54]
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	[55]
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	[56]
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	

References

1. Menetrey, P. Synthesis of punching failure in reinforced concrete. *Cem. Concr. Compos.* **2002**, *24*, 497–507. [CrossRef]
2. Abbasi, M.; Baluch, M.H.; Azad, A.K.; Abdelrahman, H. Nonlinear finite element modelling of failure modes in RC slabs. *Comp. Struct.* **1992**, *42*, 815–823. [CrossRef]
3. Theodorakopoulos, D.; Swamy, R. Ultimate punching shear strength analysis of slab–column connections. *Cem. Concr. Compos.* **2002**, *24*, 509–521. [CrossRef]
4. Metwally, I.M.; Issa, M.S.; El-Betar, S.A. Punching shear resistance of normal and high strength reinforced concrete flat slabs. *Civ. Eng. Res. Mag.* **2008**, *30*, 982–1004.
5. Micallef, K.; Sagaseta, J.; Ruiz, M.F.; Muttoni, A. Assessing punching shear failure in reinforced concrete flat slabs subjected to localised impact loading. *Int. J. Impact Eng.* **2014**, *71*, 17–33. [CrossRef]
6. ACI. *Building Code Requirements for Reinforced Concrete*; American Concrete Institute: Farmington Hills, MI, USA, 2014.
7. BS. *Structural Use of Concrete. Part I: Code of Practice for Design and Construction*; British Standards Institution: London, UK, 1997.
8. FIB, M.C. *Model Code 2010–Final Draft, Vol, 1*; Bulletins: Lausanne, Switzerland, 2010.
9. De Normalisation, C.E. *Eurocode 2: Design of Concrete Structures—Part 1-1: General Rules and Rules for Buildings*; European Committee for Standardization: Brussels, Belgium, 2004.
10. Shoorehdeli, M.A.; Teshnehlab, M.; Sedigh, A.K. Identification using ANFIS with intelligent hybrid stable learning algorithm approaches. *Neural Comput. Appl.* **2009**, *18*, 157–174. [CrossRef]
11. Kasperkiewicz, J.; Racz, J.; Dubrawski, A. HPC strength prediction using artificial neural network. *J. Comput. Civ. Eng.* **1995**, *9*, 279–284. [CrossRef]
12. Takagi, T.; Sugeno, M. Fuzzy identification of systems and its applications to modeling and control. *IEEE Trans. Syst. Man Cybern.* **1985**, *1*, 116–132. [CrossRef]
13. Topçu, İ.B.; Sarıdemir, M. Prediction of rubberized concrete properties using artificial neural network and fuzzy logic. *Constr. Build. Mater.* **2008**, *22*, 532–540. [CrossRef]
14. Bilgehan, M. Comparison of ANFIS and NN models—With a study in critical buckling load estimation. *Appl. Soft Comput.* **2011**, *11*, 3779–3791. [CrossRef]
15. Tesfamariam, S.; Najjaran, H. Adaptive network–fuzzy inferencing to estimate concrete strength using mix design. *J. Mater. Civ. Eng.* **2007**, *19*, 550–560. [CrossRef]
16. Akbulut, S.; Hasiloglu, A.S.; Pamukcu, S. Data generation for shear modulus and damping ratio in reinforced sands using adaptive neuro-fuzzy inference system. *Soil Dyn. Earthq. Eng.* **2004**, *24*, 805–814. [CrossRef]
17. Inan, G.; Göktepe, A.B.; Ramyar, K.; Sezer, A. Prediction of sulfate expansion of PC mortar using adaptive neuro-fuzzy methodology. *Build. Environ.* **2007**, *42*, 1264–1269. [CrossRef]
18. Fonseca, E.T.; g da s Vellasco, P.C.; Vellasco, M.M.B.R.; de Andrade, S.A.L. A neuro-fuzzy evaluation of steel beams patch load behaviour. *Adv. Eng. Softw.* **2008**, *39*, 558–572. [CrossRef]
19. Wang, Y.-M.; Elhag, T.M. An adaptive neuro-fuzzy inference system for bridge risk assessment. *Expert Syst. Appl.* **2008**, *34*, 3099–3106. [CrossRef]
20. Bateni, S.; Jeng, D.-S. Estimation of pile group scour using adaptive neuro-fuzzy approach. *Ocean Eng.* **2007**, *34*, 1344–1354. [CrossRef]
21. Mashrei, M.A. Prediction of the Shear Strength of Concrete Beams Reinforced with Fiber Reinforced Polymer Bars Using Artificial Neural Networks Model. *Thi-Qar Univ. J. Eng. Sci.* **2011**, *2*, 45–63.
22. Bilgehan, M.; Kurtoğlu, A.E. ANFIS-based prediction of moment capacity of reinforced concrete slabs exposed to fire. *Neural Comput. Appl.* **2016**, *27*, 869–881. [CrossRef]
23. Mansouri, I.; Kisi, O.; Sadeghian, P.; Lee, C.-H.; Hu, J.W. Prediction of ultimate strain and strength of FRP-confined concrete cylinders using soft computing methods. *Appl. Sci.* **2017**, *7*, 751. [CrossRef]
24. Naderpour, H.; Poursaeidi, O.; Ahmadi, M. Shear Resistance Prediction of Concrete Beams Reinforced by FRP Bars Using Artificial Neural Networks. *Measurement* **2018**. [CrossRef]
25. Basarir, H.; Bin, H.; Fourie, A.; Karrech, A.; Elchalakani, M. An adaptive neuro fuzzy inference system to model the uniaxial compressive strength of cemented hydraulic backfill. *Min. Miner. Depos.* **2018**, *12*, 1–12. [CrossRef]

26. Dönmez, A.; Bažant, Z.P. Size effect on punching strength of reinforced concrete slabs with and without shear reinforcement. *ACI Struct. J.* **2017**, *114*, 875. [CrossRef]
27. Shehata, I.A. Simplified model for estimating the punching resistance of reinforced corete slabs. *Mater. Struct.* **1990**, *23*, 364–371. [CrossRef]
28. Regan, P.E. *Behaviour of Reinforced Concrete Flat Slabs*; Construction Inudstry Research and Information Association: London, UK, 1981.
29. Gardner, N. Size Effect on Punching Strength of Reinforced Concrete Slabs with and without Shear Reinforcement. *ACI Struct. J.* **2018**, *115*, 897–899.
30. Bazant, Z.P.; Kim, J.K. Size effect in shear failure of longitudinally reinforced beams. *J. Am. Concr. Inst.* **1984**, *81*, 456–468.
31. Demirkaya, S. Deformation analysis of an arch dam using ANFIS. In Proceedings of the Second International Workshop on Application of Artificial Intelligence and Innovations in Engineering Geodesy, Braunschweig, Germany, June 2010.
32. Chang, F.J.; Chang, Y.T. Adaptive neuro-fuzzy inference system for prediction of water level in reservoir. *Adv. Water Resour.* **2006**, *29*, 1–10. [CrossRef]
33. Xu, J.; Wang, X.L. Prediction of Concrete Strength Using Fuzzy Neural Networks. *Adv. Mater. Res.* **2011**, *243*, 6121–6126. [CrossRef]
34. Jang, J.S. ANFIS: Adaptive-network-based fuzzy inference system. *IEEE Trans. Syst. Man Cybern.* **1993**, *23*, 665–685. [CrossRef]
35. Mamdani, E.H. Application of fuzzy algorithms for control of simple dynamic plant. *Proc. Electr. Eng.* **1974**, *121*. [CrossRef]
36. Sugeno, M.; Tanaka, K. Successive identification of a fuzzy model and its applications to prediction of a complex system. *Fuzzy Sets Syst.* **1991**, *42*, 315–334. [CrossRef]
37. Sugeno, M.; Kang, G. Structure identification of fuzzy model. *Fuzzy Sets Syst.* **1988**, *28*, 15–33. [CrossRef]
38. Zadeh, L.A. Information and control. *Fuzzy Sets* **1965**, *8*, 338–353.
39. *MATLAB, V. 8.1. 0.604 (R2013a)*; MathWorks: Natick, MA, USA, 2013.
40. Marzouk, H.; Hussein, A. Experimental investigation on the behavior of high-strength concrete slabs. *ACI Struct. J.* **1991**, *88*, 701–713.
41. Mowrer, R.; Vanderbilt, M. Shear strength of lightweight aggregate reinforced concrete flat plates. *J. Am. Concr. Inst.* **1967**, *64*, 722–729.
42. Kinnunen, S.; Nylander, H.; Tolf, P. Investigations on Punching at the Division of Building Statics and Structural Engineering. *Nordisk Betong* **1978**, *3*, 25–27.
43. Elstner, R.C.; Hognestad, E. Shearing strength of reinforced concrete slabs. *J. Proc.* **1956**, *53*, 29–58.
44. Moe, J. *Shearing Strength of Reinforced Concrete Slabs and Footings under Concentrated Loads*; Portland Cement Association, Research and Development Laboratories: Chicago, IL, USA, 1961.
45. Regan, P.; Walker, P.; Zakaria, K. *Tests of Reinforced Concrete Flat Slabs*; CIRIA Project RP; Polytechnic of Central: London, UK, 1979; 220p.
46. Rankin, G.; Long, A. Predicting the Punching Strength of Conventional Slab-Column Specimens. *Proc. Inst. Civ. Eng.* **1987**, *82*, 327–346. [CrossRef]
47. Gardner, N. Relationship of the punching shear capacity of reinforced concrete slabs with concrete strength. *Struct. J.* **1990**, *87*, 66–71.
48. Tomaszewicz, A. *Punching Shear Capacity of Reinforced Concrete Slabs*; Trondheim SINTEF: Trondheim, Norway, 1993; 36p.
49. Ramdane, K. Punching shear of high performance concrete slabs. In Proceedings of the Fourth International Symposium on Utilization of High-Strength/High Performance Concrete, Paris, France, 29–31 May 1996.
50. Hallgren, M. *Punching Shear Capacity of Reinforced High Strength Concrete Slabs*; KTH Byggvetenskap: Stockholm, Sweden, 1996.
51. Kevin, K. *Influence of Size on Punching Shear Strength of Concrete Slabs*; McGill University: Montreal, QC, Canada, 2000; p. 92.
52. Guandalini, S.; Muttoni, A. *Symmetrical Punching Tests on Slabs without Transverse Reinforcement*; Test Report; de Lausanne Institut: Lausanne, Switzerland, 2004.

53. Sundquist, H.; Kinnunen, S. *The Effect of Column Head and Drop Panels on the Punching Capacity of Flat Slabs*; Bulletin No. 82; Department of Civil and Architectural Engineering, Royal Institute of Technology: Stockholm, Sweden, 2004.
54. Birkle, G.; Dilger, W.H. Influence of slab thickness on punching shear strength. *ACI Struct. J.* **2008**, *105*, 180–188.
55. Marzouk, H.; Hossin, M. *Crack Analysis of Reinforced Concrete Two-Way Slabs*; Research Report; Faculty of Engineering and Applied Science, Memorial University of Newfoundland: St. John's, NL, Canada, 2007.
56. Marzouk, R.; Rizk, E. *Punching Analysis of Reinforced Concrete Two-Way Slabs*; Research Report RCS01; Faculty of Engineering and Applied Science, Memorial University of Newfoundland: St. John's, NL, Canada, 2009.
57. Chiu, S.L. Fuzzy model identification based on cluster estimation. *J. Int. Fuzzy Syst.* **1994**, *2*, 267–278.
58. Mashrei, M.A.; Abdulrazzaq, N.; Abdalla, T.Y.; Rahman, M.S. Neural networks model and adaptive neuro-fuzzy inference system for predicting the moment capacity of ferrocement members. *Eng. Struct.* **2010**, *32*, 1723–1734. [CrossRef]