Predicting Punching Shear Strength of Ferrocement Slabs Using Back-Propagation Neural Network

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Abstract

A back-propagation neural network (BPNN) model is developed to predict the punching shear strength of square ferrocement slabs. The experimental data used for training and testing the neural network model, are collected from several sources. They are arranged in a format of seven input parameters (the effective span, slab thickness, yield tensile strength of wire mesh, volume fraction of wire mesh, mortar compressive strength, width of square loaded area, boundary condition of the supported slabs) and one output parameter (punching shear strength). A parametric study is carried out using BPNN to study the influence of each parameter affecting the punching shear strength of ferrocement slabs. A comparison with the experimental results and those from other existing empirical equations demonstrates that the predictions from BPNN are indeed better. We conclude that the BPNN model may serve as a good tool for predicting the punching shear strength.

***Keywords*: Ferrocement; Punching shear; Slabs; Strength; BPNN.**

التنبؤ بمقاومة القص للسقوف الفيروسمنتية باستخدام تقنيات الشبكات العصبية

المستخلص

استخدمت خوارزمية التعقب الخلفي للشبكات العصبية للتنبؤ بمقاومة القص للسقوف الفيروسمنتية ذات الاشكال **المربعة**. تم تدريب وفحص الشبكة العصبية بالاعتماد على معلومات عملية **أخذت من تجارب سابقة ومن مصادر مختلفة**. تم الأخذ بنظر الاعتبار العوامل المؤثرة هندسيا على تصرف السقوف بشكل عام لبناء الشبكة العصبية. **مدخلات الشبكة** هي: **الفضاء الفعال, سمك السقف, مقاومة الخرسانة,** نسبة الحديد, مقدار الخضوع للحديد, ابعاد مساحة التحميل بالإضافة إلى طريقة الإسناد المستخدمة أما المخرجات فكانت مقاومة القص للسقوف. كذلك تم في هذا البحث دراسة تأثير كل عنصر من العناصر المدخلة على مقاومة القص للسقوف الفيروسمنتية. تم مقارنة النتائج التي تم الحصول عليها في بحثنا هذا مع بعض النتائج العملية و مع النتائج التي تم الحصول عليها من طرق مقترحة اخرى لحساب مقاومة القص للسقوف. **اثبت** النتائج بان تقنية الشبكات العصبية وباستخدام خوارزمية التعقب الخلفي هي طريقة جيدة لحساب مقاومة القص ويمكن اعتمادها للتبوء بأي نموذج أخرى ضمن حدود البيانات المستخدمة في بحثنا هذا.

1. Introduction

With the rapid progress in innovative construction techniques, application of ferrocement is becoming increasingly common for use in various structural engineering applications. This has led significant research activities for this material resulting in considerable volume of technical information on design, construction, maintenance and rehabilitation techniques using ferrocement.

Ferrocement is a composite material constructed by cement mortar reinforced with closely spaced layers of wire mesh [1-5]. The ultimate tensile resistance of ferrocement is provided solely by the reinforcement in the direction of loading. The compressive strength is equal to that of the unreinforced mortar. However, the analysis and design of ferrocement elements is complex and is based primarily on the reinforced concrete analysis using the principles of equilibrium and compatibility [6]. Most of the applications of ferrocement is in civil engineering structures are for the situations where high tensile strength or small crack width is the governing criteria. Also the use of ferrocement is not limited to stressed skin elements alone. In applications with ferrocement as plate structural elements, it becomes necessary to understand the punching shear behavior of ferrocement. There are few papers available in the literature on the behavior of ferrocement slabs under punching shear. Paramasivam and Tan [7] presented an experimental study to evaluate the punching shear strength of ferrocement slabs. They considered the effect of the effective span to depth ratio, thickness of the slab, volume fraction of reinforcement, mortar strength, size of the load bearing plate and the spacing of the skeletal steel. Mansur et al. [8] considered a tests on 31 simply supported square ferrocement slabs under a central concentrated load to estimate the punching shear. All slabs failed in punching shear. Authors found that the punching shear increased with an increase in the thickness of the slab, volume fraction of reinforcement, mortar strength, size of the load bearing plate and decrease as the effective span is increased. Based on the experimental results, they developed an empirical formula to estimate the punching shear strength. Al-Kubaisy and Jumaat [9] presented a study on the behavior of simply supported ferrocement slabs under punching shear. The effects of the parameters as presented in [7] and shape of the loading area on the punching shear strength are examined. Mansur et al. [10] carried out an experimental study on a 14 restrained ferrocement slabs under a central load. The slab are supported and restrained on all four sides by edge ribs. They investigated the punching shear strength of slab and effect of the degree of the end restrained in adding to the effect of thickness of slab, mortar strength, size of loaded area and volume fraction of reinforcement.

The relationships used to estimate the punching shear strength are empirical formula and their predictive abilities are limited by the corresponding data sets from which they are derived. In some cases, these methods do not provide reliable predictions for use in practice. Over the last few years or so, the use of an alternative approach to modeling based on artificial neural networks (ANNs) has increased in many areas of engineering. In particular, ANNs have been applied to many structural and geotechnical engineering problems. Neural networks are an observational model developed on the basis of available data representing a mapping between input and output variables. The main advantage of ANNs is that one does not require an explicit model or equation, which is a prerequisite in the conventional approach [11]. In other words, when the information available for constructing the model is only available in the form of data derived from observations or measurements, neural network models, based on the input/output variables systems, have been successfully used to generate the relationships between these variables. The typical ANN model consists of a number of artificial neurons variously known as processing elements or nodes that are usually arranged in layers, more information on the use of ANN models in engineering applications may be found in ([12,13]. Back-propagation neural network are the most commonly used type of networks in structural engineering applications where a set of input parameters are mapped through single or several hidden layers, using weights, into output parameters.

The purpose of this study is to develop a BPNN based model to evaluate the punching shear strength of ferrocement slabs. The performance of the BPNN model is compared with experimental data and other empirical models. The developed BPNN model is also utilized to evaluate the effect of various variables which govern the behavior of such structure. The study is based on an available database resulting from tests on 68 specimens.

2. Existing models to estimate punching shear strength

Several models have been proposed to theoretically predict the punching shear strength of ferrocement slab. A brief summary of select models only are given in the following:

2.1- ACI building code equations[14]

The punching shear strength of ferrocement slabs was estimated using the equation proposed for reinforced concrete by ACI 318 code. The punching shear strength (V_u) is taken as the smallest of the following

$a)$ $$V_u = \left(2 + \frac{4}{\beta}\right)\sqrt{f_c'}\, u_o\, d \qquad (1)$$

b) $$V_u = \left(\frac{\alpha_s\, d}{u_o} + 2\right)\sqrt{f_c'}\, u_o\, d \tag{2}$$

c) $$V_u = 4\sqrt{f_c'}\, u_o\, d \tag{3}$$

2.2-Al-Kubaisy and Jumaat equation[9]

An empirical equation is proposed by Al-Kubaisy and Jumaat to predict the punching shear strength based on tested ferrocement slabs. The proposed equation can be written as

$$V_u = u_{cr}\,.\,d.\,[0.07(f_{cu})^{0.5} + 0.35(\rho)^{1.1}](\frac{h}{30} + 0.2)^{1.25}\,(\frac{100}{a})^{0.5} \tag{4}$$

where:

$$u_{cr} = 4[0.75a + \frac{5.32.h + 0.25a}{\sqrt{2}}]$$

f_{cu}: cube compressive strength ≤ 60 N/mm^2

ρ: $100\, A_s/b.d\ \leq 3$

h: total thickness ≤ 30mm

a: side dimension of a square loaded area or equivalent square for rectangular or circular loaded area

2.3-Mansur et al. equation [8]

Mansur et al. presented an empirical equation to predict the punching shear strength of ferrocement. The final expression of proposed equation is given in the following

$$V_u = 0.45\,(f_c')^{1/3}\,(v_f)^{0.5}\,(\frac{h}{l})^{1/3}.\,u_o.\,h \tag{5}$$

where

$u_o = 4(w + 2.k.h)$

$k = 1.5$

3. Neural network

3.1 Neural network architecture

A Neural network model may be thought of as black box device that accepts inputs and produces outputs [15]. The commonest type of artificial neural network consists of three groups or layers of units: input layer units connected to one or two layers of hidden units which is/are connected to a layer of output units. The function of input layer is to receive input or information from the outside world, and to pass this information to the network for processing. These may be either sensory input or signals from other systems outside the one being modeled.

The number of input neurons corresponds to the number of input variables into the neural network, and the number of output neurons is the same as the number of desired output variables. The number of neurons in the hidden layer(s) depends on the application of the network. In engineering problems, the numbers of input and output parameters are generally determined by design requirements.

As inputs enter the input layer from an external source, the input layer becomes activated and emits signals to its neighbors (hidden layer) without any modification. Neurons in the input layer act as distribution nodes and transfer input signals to neurons in the hidden layer. The neighbors receive excitation from the input layer, and in turn emit an output to their neighbors (second hidden layer or output layer). Each input connection is assigned weight factor or connection strength. The strength of a connection between two neurons determines the relative effect that one neuron can have on another.

3.2 Elements of neural networks

The basic component of a neural network is the neuron, also called node, or the processing element (PE). Nodes contain the mathematical processing elements which govern the operation of a neural network. Figure 1 illustrates a single node of a neural network, in which it can be distinguished:

a- Inputs and outputs

Inputs are represented by a_1, a_2, …, and a_n, and the output by b_j. Just as there are many inputs to a neuron, there should be many input signals to the PE. The PE manipulates these inputs to give a single output signal.

b- Weighting factors

The values w_{1j}, w_{2j}, …, and w_{nj} are weight factors associated with each input to the node. This is something like the varying synaptic strengths of biological neurons. Weights are adaptive coefficients within the network that determine the intensity of the input signal. Every input (a_1, a_2, …, a_n) is multiplied by its corresponding weight factor (w_{1j}, w_{2j}, …, w_{nj}), and the node uses this weighted input (w_{1j} a_1, w_{2j} a_2, …, w_{nj} a_n) to perform further calculations. For a positive weight factor, (w_{ij} a_i) tends to excite the node, and for a negative weight factor, (w_{ij} a_i) inhibits the node. In the initial setup of a neural network, weight factors may be chosen according to a specified statistical distribution. Then these weight factors are adjusted during the development of the network or learning process.

c- Internal threshold

The other input to the node is the node's internal threshold, T_j. This is a randomly chosen value that governs the activation or total input of the node through the following equation [15].

$$\text{Total activation}= X_i = \sum_{i=1}^{n} (w_{ij}\, a_i) - T_j \tag{6}$$

The total activation depends on the magnitude of the internal threshold T_j. If T_j is large or positive, the node has a high internal threshold, thus inhibiting node-firing. If T_j is zero or negative, the node has a low internal threshold, which excites node-firing [15]. If no internal threshold is specified, a zero value is assumed.

d- Transfer functions

The node's output is determined by using a mathematical operation on the total activation of the node. This operation is called a transfer function. The transfer function can transform the node's activation in a linear or nonlinear manner [15].

3.3 Training the network

Training is the process by which the neural network systematically adjusts the weights of interconnections between nodes so that the network can predict the correct outputs for a given set of inputs. There are many different types of training algorithms. One of the most common classes of training algorithms for feed-forward interlayer networks is called back-propagation. In a back-propagation algorithm, a set of inputs is fed to the network and outputs are returned. Then, the network compares its output with the output of the actual data set. The network calculates the amount of error between its predicted output and the actual output. The network works backwards through the layers, adjusting the weight factors according to how much error it has calculated in its output. Once all of the weight factors have been adjusted, the network works in a forward path, taking the same input data to predict the output, based on the new weight factors. The network again calculates the error between the predicted and actual outputs. It adjusts the weight factors and the process continues iteratively, until the error between the predicted and actual outputs has been minimized.

3.4 Generalization

After learning or training, the network should extract regularities or rules from the training data and be able to generalize (during testing), to give the right answers for input not belonging to the training sets. When the network is trained with a randomly selected set of examples and tested with another set of inputs, the expected number of correct results is called generalization capability. Generalization capability can be used to evaluate the behavior of the ANN [16].

4. BPNN model: This study

A BPNN model developed for this study is used to predict the punching shear strength of ferrocement slabs. The Neural Network Toolbox of MATLAB [17] is used to develop a BPNN model for this problem. The results from the available study in the literature[7-10] were used to compile a set of 68 experimental data, which is divided into two groups, one for training and another for testing.

Seven variables are selected as input to BPNN model. These variables are: the effective span (l), slab thickness (h), yield tensile strength of wire mesh (f_y), volume fraction of reinforcement (v_f), mortar compressive strength (f_c'), width of square loaded area (w), boundary condition of the supported slabs (r). The output variable is the punching shear strength of ferrocement slab. Table 1 summarizes the ranges of the different variables. The data used in this study are summarized in Table A in the Appendix.

Through a set of trials, a network of two hidden layers with five neurons in each layer was found to yield an optimal configuration, with minimum mean square error (MSE). The number of hidden layers, number of hidden nodes, and transfer functions are chosen to get the best performance of the model. After the errors are minimized, the model with all the parameters including the connection weights is tested with a separate set of testing data that is not used in the training phase. At the end of the training, the neural network represents a model that should be able to predict the target value (punching shear strength) for given the input pattern.

The network was trained continually through updating of the weights until the final error of $1.37*10^{-3}$ was achieved after 500 epochs. Figure. 2 shows the performance for training and testing data sets. The network performance with back-propagation training algorithm have been tested for training and testing patterns, as shown in Figures. 3 and 4. The predicted values were found to be in good agreement with the actual (target) values.

5. Graphical user interface (GUI) of BPNN program

The graphical user interface (GUI) developed for the BPNN program is presented in Figure. 5. GUI provides a user friendly platform run the analysis using intuitive text boxes. The GUI represents a simplified tool to use the developed neural network to predict the punching shear strength of ferrocement slab. A window is provided through which the input data is introduced and the results of network are displayed in the same window or in an output file. The results include the output of the network and the regression analysis for both the training and testing phases. The main advantage of the GUI is the short time that used to predict the punching shear strength. nine seconds is enough to get the result.

6. Parametric study

Once the artificial neural network has been trained, a parametric analysis is conducted to study the influence of the various parameters on the punching shear strength of slabs. The most important conclusions are given in the following.

In Figure (6) the punching shear strength of ferrocement slab is plotted versus the total thickness of slab (h). It can be clearly seen from the figure that an increases in h causes the punching shear strength to increase. This is so because larger h increases the stiffness and strength of slab. This conforms to the observations reported by [8-10].

Figure (7) shows the effect of compressive strength of mortar(f_c') on punching shear strength of ferrocement slab. It can be seen from this figure that as (f_c'), increases, the punching shear strength slightly increased. A reasonable agreement is achieved between the results from experiments [8,10] and those of the neural network.

The influence of the volume fraction of reinforcement (v_f) on the punching shear strength as predicted by artificial neural network is presented. Figure (8) shows that the punching shear strength can be improved substantially by an increase in v_f. In general this finding is in agreement with other experimental results [7-10].

The width of square loaded area (w) also, is important parameter, because this parameter has significant effect on behavior of ferrocement in punching shear. Figure (9) shows that the punching shear strength increases with an increase in w. This is because a larger load area required a longer critical perimeter for punching shear to occur. The increase in critical perimeter means a higher load , as also concluded by Mansur et al. [8].

The effective span (l) also has an influence on the punching shear strength of ferrocement slabs. Figure(10) shows that the relationship between the effective span and punching shear strength. It can be seen that when l decrease the shear strength increase. In other words, a decrease in the l/h ratio that achieved by changing the effective span length leads to increase the punching shear strength, but the increase is not as pronounced as in the case of changing the depth. These results are in agreement with other experimental results by [8,9].

Finally, the influence of end restraint on the punching shear strength of ferrocement slabs it may be observed in Figures(6 to 10). It can be concluded that the restrained slabs exhibited higher strength than the corresponding simply supported slabs. Mansur et al. [10] attributed that to the development of higher membrane stresses in the restrained slabs. It should be noted that the range of data of restrained slabs considered in our model is very limited because of the data available. The authors are aware of this limitation.

7. BPNN prediction: Comparison with experimental and theoretical results

The predictions of punching shear strength of ferrocement slabs as obtained from BPNN, ACI code and two empirical equation as mentioned in section 2 are compared with the experimental results and shown for both training and testing sets in Figures(11 and 12) and Table (2).

Table (2) summarizes the average and standard deviation of the ratio of the experimental punching shear strength (V_e) to predicted (V_i). The BPNN model gives an average V_e/ V_i ratio for training and test data sets of 1.0 and 1.07, and standard deviation of 0.1 and 0.14, respectively. These values indicate that the proposed BPNN model can predict more reliably the punching shear strength compared to the other three models. Figures (11 and 12) confirm the same conclusion that the predictions of BPNN model are better than those of the three empirical models. Table (3) also confirms this conclusion when comparing the correlation factor coefficient for all models for both training and test data sets. Values of 0.995 and 0.96 for the BPNN training and test data sets, respectively, are close to 1.0 and higher than that of the other three models.

8. Conclusion

In this study a model based on back-propagation neural network (BPNN) is developed to predict the punching shear strength of ferrocement slabs. A database from the results of sixty eight (68) tests is data developed from the review of literature, which is used for the training and testing of this BPNN model. Seven variables are selected as input to BPNN model with one target variable, punching shear strength.

A parametric study based on BPNN demonstrates that the network is able to learn and generalize, and thus captures quite well effect of each input variables on the final output.

The predictions of punching shear strength of ferrocement from BPNN model are compared those from three other available empirical models, as well as to those from experimental results. It is found that the predictions from BPNN are indeed better. We conclude that the BPNN model may be serve as a good tool for predicting the punching shear strength.

Table (1). Range of input parameters in the database.

No.	Parameter	Range
1	l (mm)	400-1200
2	h (mm)	10-70
3	f_c' (MPa)	21.5-72.6
4	f_y (MPa)	362-485
5	v_f	1.01-7.6
6	w (mm)	40-200
7	r	Simply supported slabs (S.S)or restrained slabs (R.S)

Table (2). Comparison of punching shear prediction.

Data set	No. Spec.	Average of V_e / V_i				STDEV of V_e / V_i			
		BPNN	ACI [14]	Mansur et al. [8]	Al Kubasy and Jumaat [9]	BPNN	ACI [14]	Mansur et al. [8]	Al Kubasy and Jumaat [9]
Training	56	1.00	0.76	1.23	1.46	0.10	0.24	0.24	0.51
Testing	12	1.07	0.81	1.26	1.45	0.14	0.22	0.20	0.42

Table (3). Comparison of correlation coefficient, R.

Model	R	
	Training	Testing
BPNN	0.995	0.96
ACI [14]	0.89	0.79
Al Kubasy and Jumaat [9]	0.89	0.74
Mansur et al. [8]	0.96	0.92

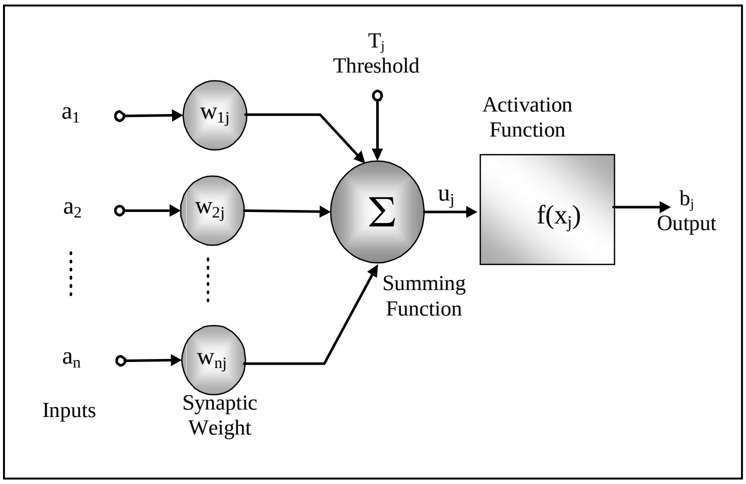


Figure (1). Single node of a neural network.

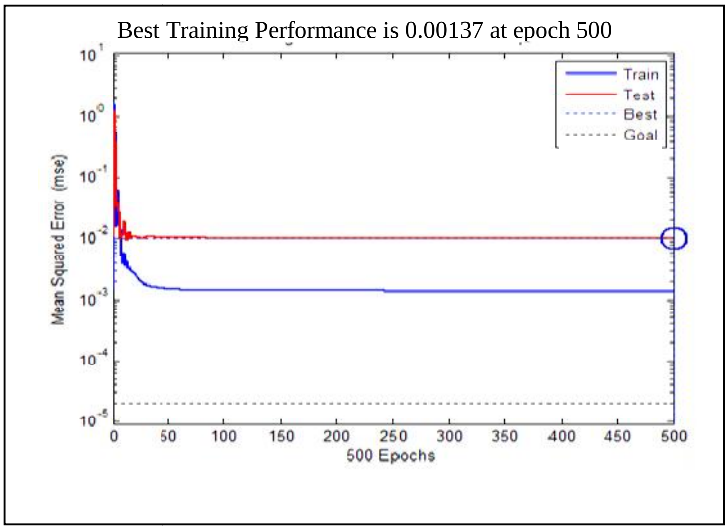
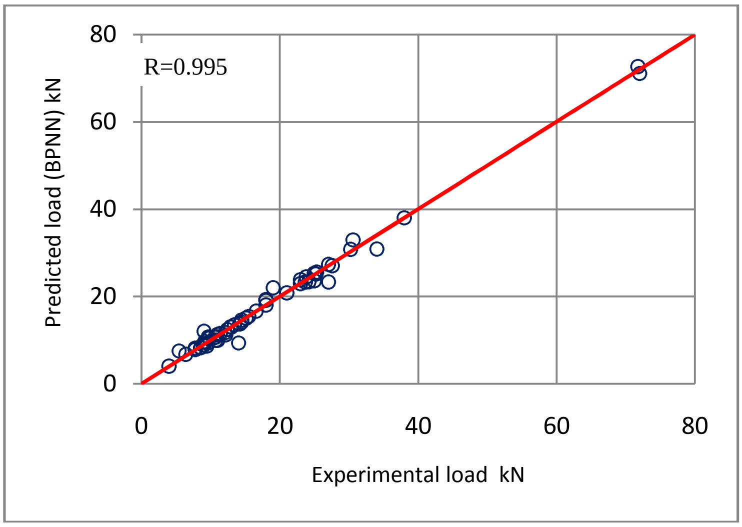


Figure (2). Convergence of the BPNN for training and testing sets.



Figure(3) .BPNN punching shear strength for training data set.

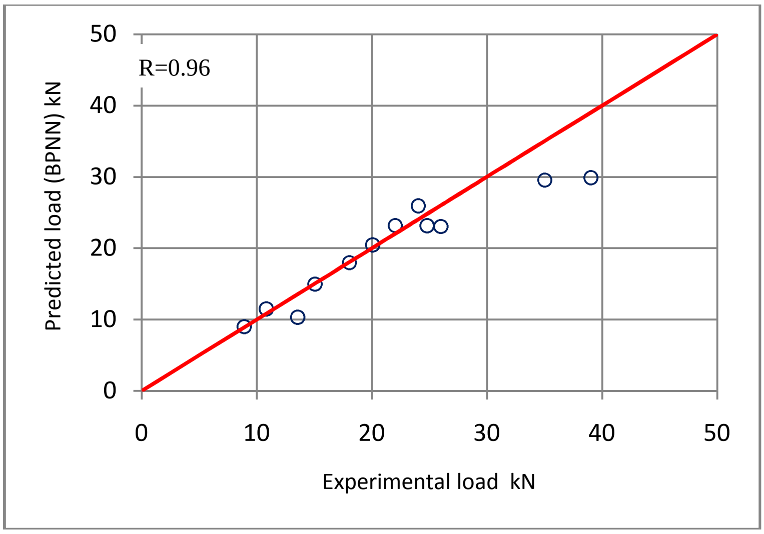


Figure (4). BPNN punching shear strength for testing data set.

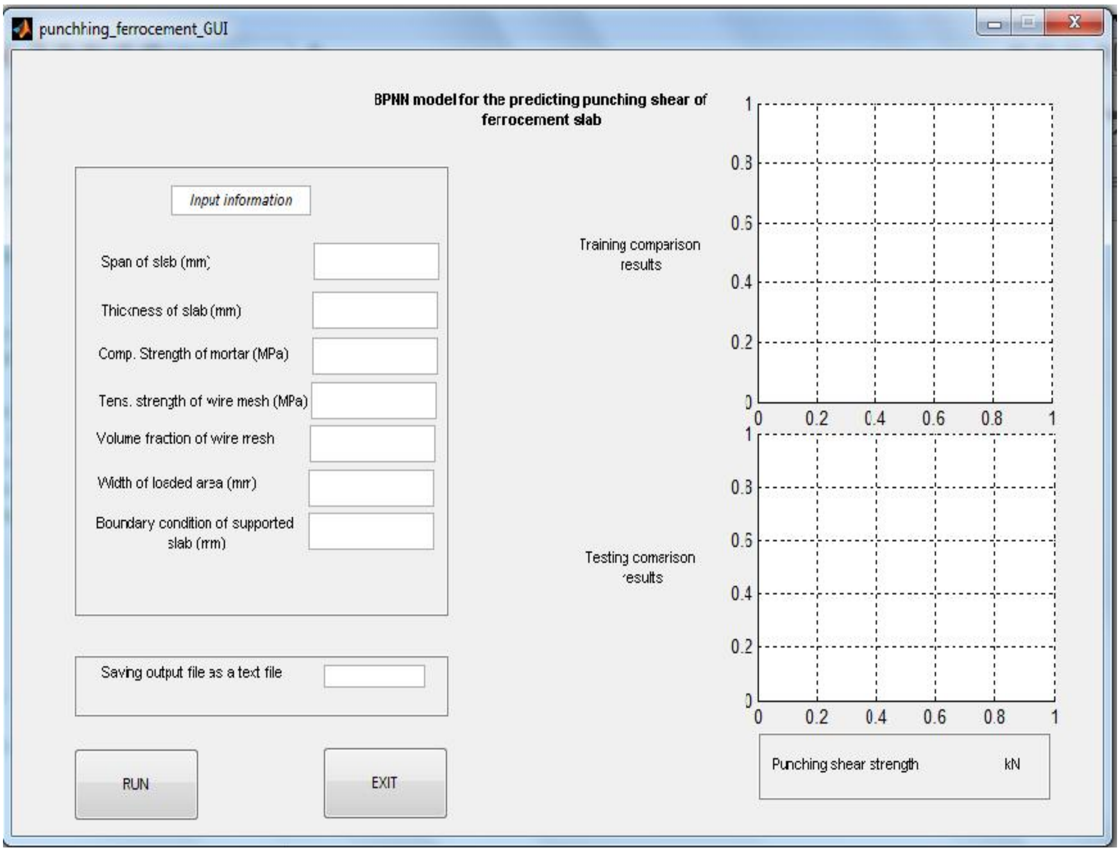


Figure (5). User friendly GUI for BPNN model.

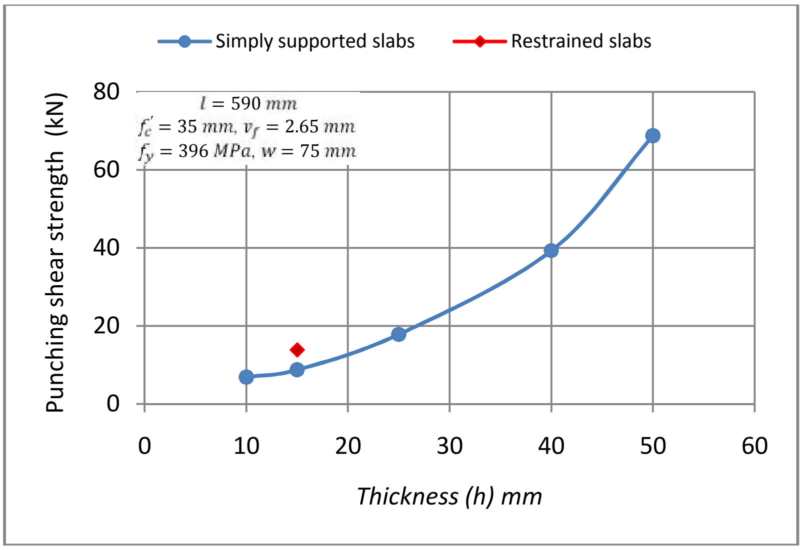


Figure (6). Effect of slab thickness on Punching shear strength.

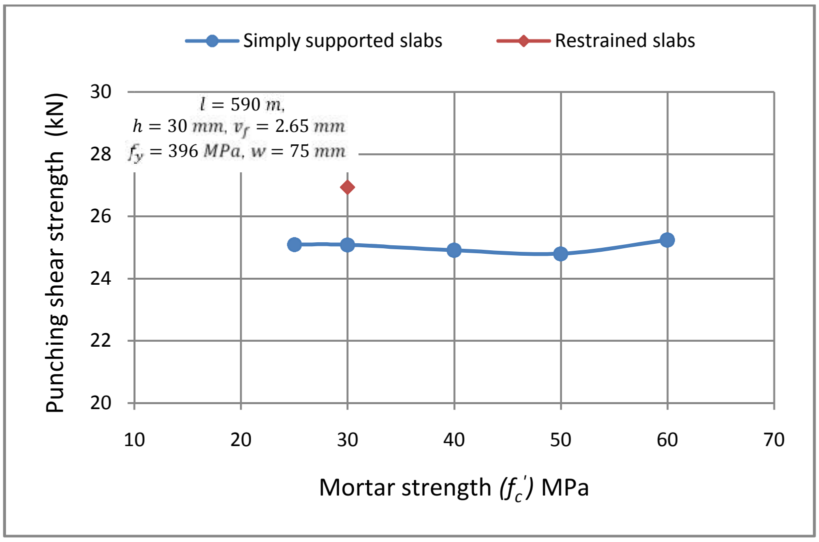


Figure (7). Effect of mortar compressive on strength punching shear strength.

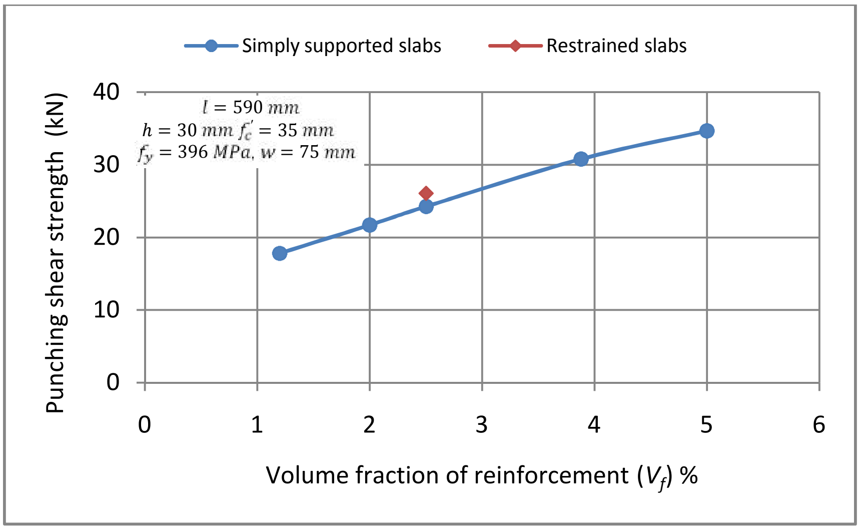


Figure (8). Effect volume fraction on punching shear strength.

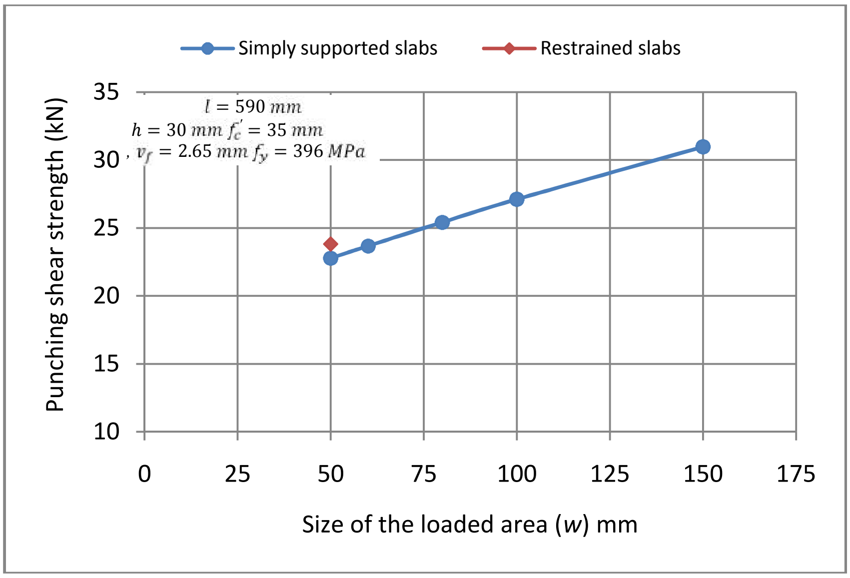


Figure (9). Effect of size of loaded area on punching shear strength.

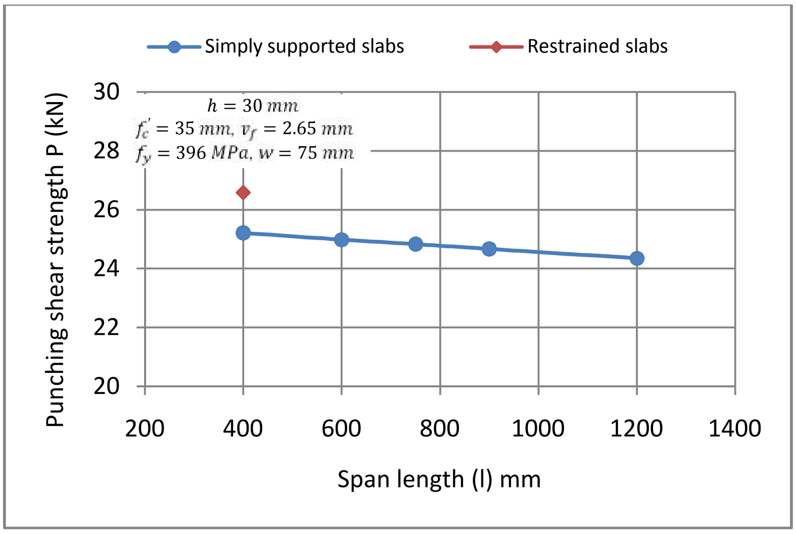


Figure (10). Effect of span length on punching shear strength.

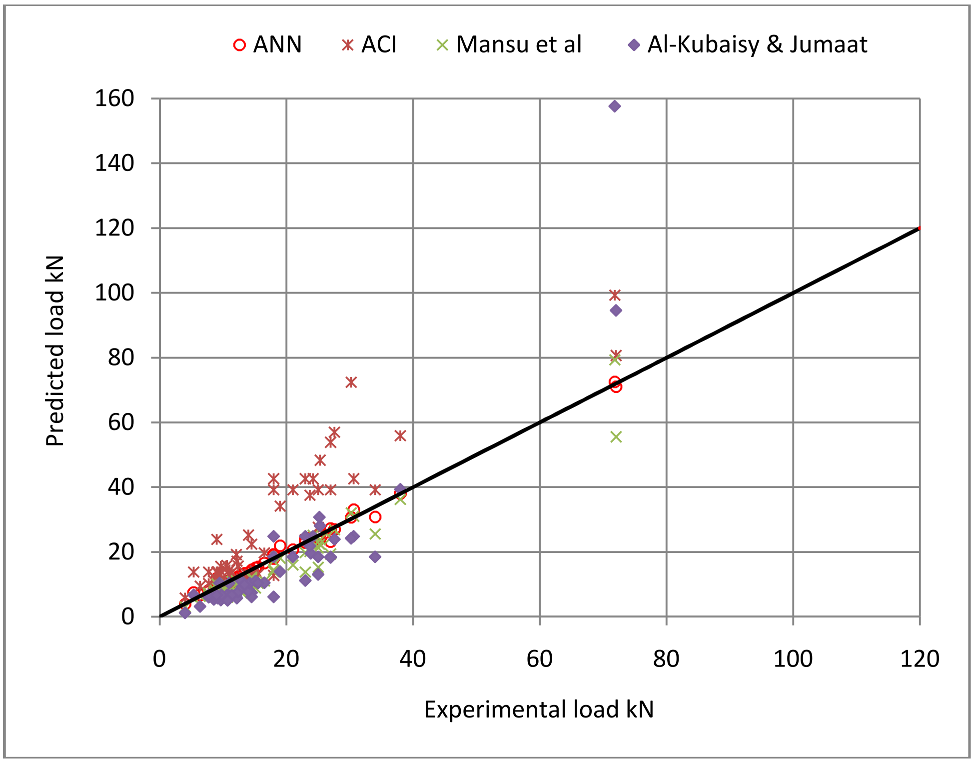


Figure (11). Experimental versus predicted punching shear for training data sets.

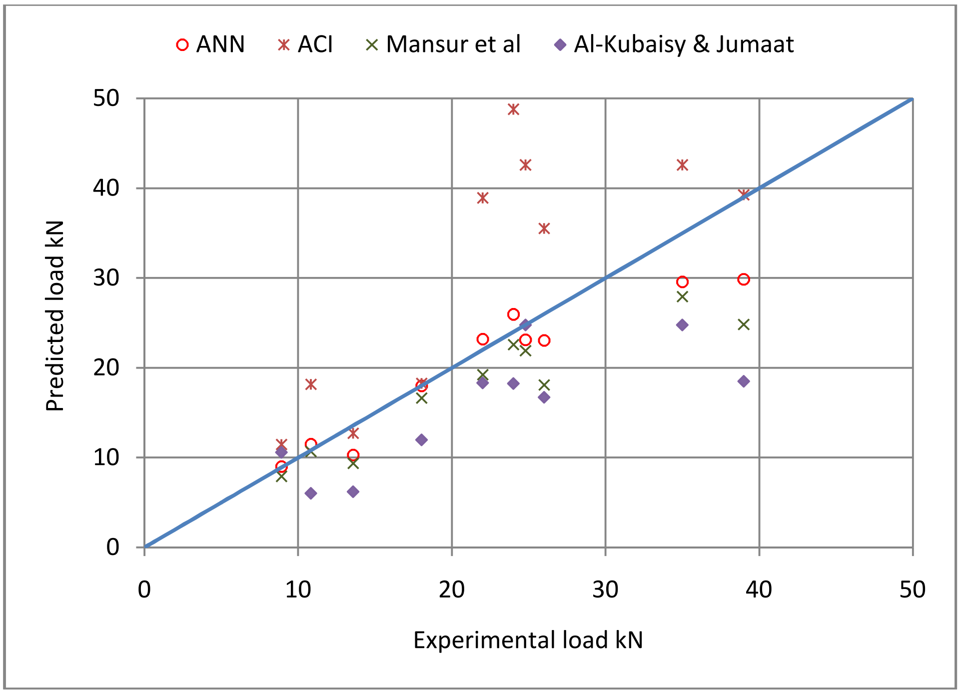


Figure (12). Experimental versus predicted punching shear for testing data sets.

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10. Notation

A_s: cross-sectional area of reinforcement (wire mesh)

b:side dimension of square slab

d : effective depth of slab

f_c': compressive strength of mortar

f_y : yield strength of wire mesh

h:total depth of slab

l: span length

r: boundary condition of the supported slabs

u_o: rectangular critical perimeter at distance 0.5d from face of column

V_u: punching shear strength

v_f: volume fraction of wire mesh

w :size of loaded area

α_s: constant used to compute shear strength in slab

β: ratio of long to short sides of the loaded area or column

ρ: reinforcement ratio

Appendix

Table (A). Experimental data used to construct the BPNN model

Test No.	l mm	h mm	f_c' MPa	f_y MPa	v_f mm	w mm	r mm	V_u kN	References
1	400	20	47.5	364	2.53	40	S.S	9.45	Mansur et al. [8]
2	400	20	52.7	364	2.53	40	S.S	8.9	
3	400	20	47.5	364	2.53	80	S.S	10.82	
4	400	20	57	364	2.53	50	S.S	10.75	
5	400	20	47.5	364	2.53	50	S.S	9.48	
6	400	20	57	364	2.53	60	S.S	10.63	
7	400	20	47.5	364	2.53	60	S.S	11	
8	400	20	52.7	364	2.53	80	S.S	12.06	
9	400	20	35.2	364	2.53	50	S.S	8.55	
10	400	20	35.2	364	2.53	80	S.S	9.68	
11	400	20	42.8	364	2.53	40	S.S	7.76	
12	400	20	42.8	364	2.53	50	S.S	8.82	
13	400	20	42.8	364	2.53	60	S.S	9.17	
14	400	20	42.8	364	2.53	80	S.S	12.16	
15	400	20	72.6	364	2.53	50	S.S	12.38	
16	400	20	72.6	364	2.53	80	S.S	14.5	
17	400	20	56.5	413	1.01	50	S.S	5.39	
18	400	20	56.5	362	1.93	50	S.S	9.75	
19	400	20	47.5	365.5	3.16	50	S.S	13.56	
20	400	25	54.7	362	3.86	50	S.S	18.02	

21	400	20	47.5	364	5.06	50	S.S	14.5	
22	400	20	47.5	364	7.6	50	S.S	18	
23	400	10	54.7	362	3.86	50	S.S	3.99	
24	400	15	54.7	362	3.86	50	S.S	6.37	
25	400	20	54.7	362	3.86	50	S.S	11.38	
26	400	30	54.7	362	3.86	50	S.S	23.84	
27	600	20	56.5	364	2.53	50	S.S	9	
28	900	20	56.5	364	2.53	50	S.S	7.76	
29	600	35	46.6	485	1.94	100	S.S	24.2	Paramasivam and Tan [7]
30	1200	35	46.6	485	1.94	100	S.S	23	
31	900	35	46.6	485	1.21	100	S.S	18	
32	900	35	46.6	485	3.88	100	S.S	30.6	
33	900	22	50.64	485	1.94	100	S.S	14	
34	900	57	46.6	485	1.94	100	S.S	72	
35	900	70	40	485	1.94	100	S.S	71.8	
36	900	35	36.4	485	1.94	100	S.S	23.7	
37	900	35	60	485	1.94	100	S.S	25.3	
38	900	35	44.6	485	1.94	200	S.S	30.2	
39	900	35	46.6	485	1.94	100	S.S	24.8	
40	900	35	46.6	485	3.15	100	S.S	35	
41	900	35	44.6	485	1.94	150	S.S	27.6	
42	750	30	58.24	406	3.55	100	S.S	34	Al-Kubaisy and Jumaat [9]
43	750	30	58.24	406	2.44	100	S.S	25	
44	750	30	58.24	403	2.03	100	S.S	27	
45	750	30	58.24	390	1.4	100	S.S	21	
46	750	30	58.24	390	1.05	100	S.S	18	
47	750	20	57.28	409	2.38	100	S.S	9	
48	750	27	57.28	399	2.61	100	S.S	19	
49	750	40	57.28	406	2.5	100	S.S	38	
50	750	30	21.5	403	2.03	100	S.S	23	
51	750	30	29	403	2.03	100	S.S	25	
52	750	30	57.12	403	2.03	150	S.S	27	
53	750	30	58.24	406	3.34	100	S.S	39	
54	750	30	47.7	403	2.03	100	S.S	26	
55	750	30	57.12	403	2.03	133	S.S	24	
56	750	30	57.12	403	2.03	100	S.S	22	
57	420	20	55.6	364	2.53	40	R.S	12.9	Mansur et al. [10]
58	420	20	50.8	364	2.53	50	R.S	14.2	
59	420	20	56.3	364	2.53	80	R.S	16.54	
60	420	20	33.4	364	2.53	50	R.S	12.97	
61	420	20	43.5	364	2.53	50	R.S	13.4	
62	420	20	60	364	2.53	50	R.S	15.13	
63	420	20	50.8	364	1.93	50	R.S	10.95	
64	420	20	50.8	364	3.86	50	R.S	15.51	
65	440	15	50.8	364	3.86	50	R.S	10.71	
66	440	30	50.8	364	3.86	50	R.S	25.21	
67	420	20	55.6	364	2.53	60	R.S	15.06	
68	440	25	50.8	364	3.86	50	R.S	20.06	