Artificial Neural Network Modelfor Shear Strengthof Fibrous RC Beams

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Abstract:

This study has investigated the modeling of shear strength using the artificial neural network (ANN) approach. The Results of 128 samples of steel fiber reinforced concrete (SFRC) beams without stirrups were collected gathered and used to generate a four-layer feed forward neural network using the back-propagation learning algorithm available in the MATLAB program. Nine parameters for SFRC beams, namely, beam height, beam depth, beam width, steel cross-sectional area, shear span-to-depth ratio, concrete compressive strength, volume fraction, fiber length, and fiber diameter, were considered as input variables for the ANN. ANN output representing the shear strength were compared with those observed experimentally using regression analysis approach. Results indicated that the ANN modeling technique is effective in simulating the behavior of SFRC beams. In addition, a parametric study shows that shear span, compressive strength of concrete, volume fraction, and fiber length are playing the major role in the behavior of SFRC beams.

Keyword: ANN model; Reinforced concrete; Shear strength; Steel fiber; Stirrups

نموذج الشبكة العصبية الاصطناعية لمقاومة القص للعتبات الخرسانية المسلحة بالألياف الفولاذية

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الخلاصة:

هذه الدراسة تتحرى نمذجة مقاومة القص باستخدام الشبكات العصبية الاصطناعية حيث جمعت نتائج 128 نموذج لعتبات خرسانية مسلحة بالالياف الفولاذية بدون حلقات القص واستخدمت لبناء نموذج الشبكات العصبية ذو اربع طبقات باستخدام طريقة التغذية الامامية وخوارزمية الانتشار العكسي التقليدية المتوفرة في برنامج (MATLAB).

تم في هذه الدراسة استخدام تسعة خصائص للعتبات الخرسانية المسلحة بالالياف الفولاذية كمدخلات وهي ارتفاع العتبة ،عمق العتبة،عرض العتبة، مساحة حددي التسليح، نسبة ذراع القص الى العمق، مقاومة انضغاط الخرسانة،النسبة الحجمية للالياف، طول وقطر الليف فيها كانت مقاومة القص للعتبة هي مخرج الشبكة. قورنت نتائج الشبكة الاصطناعية مع تلك المقاسة .(Regression Analysis) باستخدام طريقة التحليل الارتدادي.

اظهرت النتائج بان طريقة الشبكات العصبية الاصطناعية قادرة على تمثيل تصرف العتبات الخرسانية المسلحة بالالياف الفولاذية من ناحية مقاومة القص. اضافة الى ذلك بينت دراسة المقارنة بان فضاء القص، مقاومة الانضغاط للخرسانة النسبة الحجمية للالياف المستخدمة وطول اليف هي من العوامل الرئيسية التي تؤثر على تصرف العتبات الخرسانية المسلحة بالالياف الفولاذية في القص.

الكلمات الدالة. نموذج الشبكة العصبية الاصطناعية، خرسانة مسلحة ،مقاومة القص ،الليف الفولاذي ، حلقات
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1. INTRODUCTION

In modern time, has augmented the development of new materials and manufacturing methods in the field of construction. One of the most important methods in this camp is the use of steel fibers for various applications. Steel fibers have proved rather effectives' crack controlling reinforcement, particularly in slabs, due to its ability to distribute and prevent the appearance of cracks. By replacing parts of the conventional reinforcement with steel fibers, it can be developed a new, more rational production method. The innovation of more applications for steel fibers reinforced concrete (SFRC) which lead to increased research efforts is due to the beneficial properties of steel fibers. Shear reinforcement in concrete beams is an area where steel fibers may prove effective. It is incontestable the utility of fiber reinforced concrete (FRC) in various civil engineering applications. For this reason, FRC has been used successfully in slabs on grade, shot-concrete, architectural panels, precast products, offshore structures, seismic region structures, thin and thick repairs, crash barriers, footings, hydraulic structures, and many other applications.

Neural network is a computational mechanism that can obtain, represent and compute a mapping from a multivariate space of information to another given a set of data representing that mapping. The algorithm of back-propagation learning is widely used because of the simplicity of methodology.

Neural network is composed of interconnected nodes or simple neurons. These neuron connections have weights that are adapted (trained) to improve the neural networks overall performance. In back-propagation neural network, neurons are arranged in layers and are connected; thus, in a layer neurons receive input from the previous level and send output to the following level. External inputs are applied on the first layer and system outputs are taken from the last layer. Intermediate layers are called hidden layers [1].

Back-propagation neural networks (BPNNs) [2] are capable to learn from the examples of training and find meaningful solutions without the need to specify the relationship between the variables. They can capture complex and non-linear interactions between the variables in a system. Therefore, BPNNs are useful for finding solutions to the problems that lack understanding of physical understanding or those whose behaviors are not well understood. The capability of neural networks to find meaningful patterns in often-noisy data is an added advantage.

Neural network modeling technique has been applied successfully to many structural engineering problems, such as. Shear strength of RC deep beams [3]. Thickness rectangular plates [4]. Parameter identification in elasto-plastic plates [5]. Strength prediction of a concrete mix [6]. Modeling of ultimate load for R.C. beams strengthened with CFRP [7]. Shear strength of reinforced concrete corbels [8]. Modeling the capacity of CFRP-confined circular concrete columns [9] and linear and nonlinear models updating of reinforced concrete T-beam bridges [10];

The current study deals with a neural network-based system as an identification technique to predict the shear strength of a rectangular beam with steel fiber as shear reinforcement without stirrups. A computer program was developed through the MATLAB program from Math Works [11].

2. Shear Strength of SFRC Beams

There are many factors affecting the ultimate shear strength of RC beams, such as: concrete tensile strength or, indirectly, concrete compressive strength, shear span-to-effective depth ratio (a/d), longitudinal reinforcement ratio (ρ), and effective depth (d). For SFRC beams, post-cracking tensile strength of SFRC is other main factor. Many investigators used to test data assert considerable reserve strength in FRC beams failing in shear after the occurrence of the first diagonal cracking. The variance is assigned to a significant post-cracking tensile strength of the FRC compared with that of non-reinforced concrete. The difference between the shear strength of RC beams with fiber and those without fibers lies in the significant post-cracking tensile strength of the FRC. The prim factors that affect the shear strength of FRC beams are volume ratio, aspect ratio, shape of the steel fiber, compressive strength of concrete, flexural reinforcement ratio, and shear span-to-depth ratio. The existent shear strength models for FRC beams without web reinforcement are shorted in Table 1. The ACI Committee 544 recommends Sharma's model, but a code-based design equation for the shear strength of FRC beams does not exist yet.

3. Performance of Neural Network Approach

Artificial neural networks (ANNs) are information-processing systems able to learn complex cause-and-effect relationships between output and input data [12]. ANN may be describe as a calculation sample based on parallel distributed processing with private properties such as the ability to learn, generalize, classify, and organize data. Fig. 1 shows a typical neural network with the input, hidden layer, and output parts.

Main neural network architectures has two types: (1) feed forward and (2) feed backward. A back propagation (BP) the first one, which is feed-forward multilayer perception, is used widely in engineering applications. The most common BP network is the one that each neuron has only one output and as many inputs as the neurons in the former layer. The network input is connected to each neuron in the first hidden layer, while each network output is connected to each neuron in the last hidden layer. Network weights are primarily set to random values, and during the network-coaching phase, new values of the network parameters (weights) are computed. The neuron outputs are calculated using

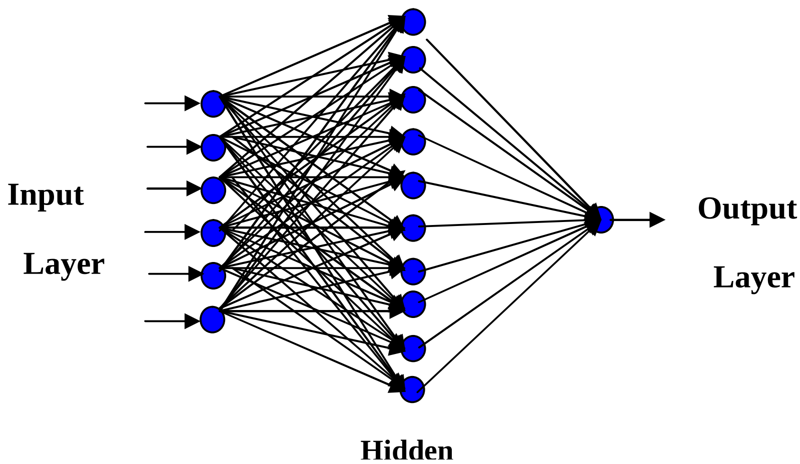

Fig. (1) Typical Neural Network Model

$$O_i = F\left(\sum_j I_j \times W_{ij} + b_i\right) \tag{1}$$

Where O_i is the output of the neuron I,Ij is the input of the j neurons of the former layer, Wij are the neuron weights; bi is the bias for modeling the threshold, and F is the activation function. The activation function can be defined as the part of the neural network where all the computing is completed. It maps the input domain (infinite) to an output domain (finite). The range to which most activation functions map their output is in either the interval [0, 1] or the interval [–1, 1].

Many activation functions have been used over the years. However, the most common activation functions belong five families to them [12]: (1) linear activation function. (2) step activation function. (3) ramp activation function. (4) sigmoid activation function. and (5) Gaussian activation function. The ANN error (E) for a given training pattern i is given by

$$E = \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{m}(O^i{}_j - T^i{}_j)^2 \tag{2}$$

Where $O^i{}_j$ is the output and Ti j is the target.

Table (1) Existing Shear Strength Models for FRC Beams Without Web Reinforcement

No.	Author	Shear strength models, MPa
1	**ACI318-08**[13]	$v_n = \left(\frac{\sqrt{f_c'}}{6}\right) b_w d \qquad f_c' < 70 MPa$ $v_n = \left(\frac{1\sqrt{f_c'}}{7} + 17\rho \frac{V_{ud}}{M}\right) b_w d \qquad f_c' < 70 MPa,\ Vd/M \le 1$
2	**Euro EC02**[14]	$v_n = 0.18k(100\rho_l f_c)^{1/3} b_w d \ge 0.035(k)^{3/2}(f_c)^{0.5} b_w d$ $f_c \le 100 MPa,\ k = 1 + \sqrt{\frac{200}{d}} \le 2.0,\ \rho_l = \frac{A_l}{b_w d} \le 0.02$
3	**Narayanan and Darwish**[15]	$v_n = e\left[0.24 f_{spfc} + 80\rho \frac{d}{a_v}\right] + 0.41\tau F$ e = 1 for a/d> 2.8e = 2.8d/a for other case
4	**Sharma**[16]	$v_n = \frac{2 f_{spfc}}{3}\left(\frac{d}{a_v}\right)^{0.25} \qquad f_{spfc} = 0.792\left(f'_{cf}\right)^{0.5}$
5	**Cladera**[17]	$v_n = \left(0.225\xi(100\rho_l)^{0.5}(f_c')^{0.2}\right) b_w d$ $\xi = 1 + \sqrt{\frac{200}{0.9d}}$

Database for Shear Strength of SFRC Beams

The publicdomain database used for this purpose was collected from previously published papers [18–35]. A total of 128 data entries were adopted covering the SFRC without stirrups and with shear failure only. The ranges of different factors affecting the shear strength of SFRC beams are shown in Table 2.

Table (2) Range of Input Parameters in the Database

Input Parameter	Minimum	Maximum		Input Parameter	Minimum	Maximum
h (mm)	100	375		$f_{c'}$*(MPa)*	22.7	101.32
d (mm)	80	290		V_f*(%)*	0.22	2
b (mm)	50	152		L_f*(mm)*	19	60
A_s*(mm²)*	71.2	1232		d_f*(mm)*	0.25	1.336
a/d	1.0	6.0		v_n *(MPa)*	0.56	13.95

4. Neural Network Models for SFRC Beams

The ANN model was constructed using nine main parameters for the input, namely, concrete strength (fc'), height beam (h), beam width (b), effective depth (d), shear span-to-depth ratio (a/d), longitudinal steel ratio (ρ), volume fraction (V_f), fiber length (lf), and fiber diameter (df). The models have two hidden layers with 27 nodes, and the output layer hasone node giving ultimate shear strength to the FRC beams. The sigmoid function was used as an activation function, and the inputs and outputswere scaled in the range of 0.1 to 0.9. Network training was performed using 111 sets of data from the literature. Network testing was done using 17 data sets randomly selected from the same sources, which are given in Table (4). Convergence of the models in training was based on minimizing the error of tolerance for the root mean squared error during the training cycles and monitoring the overall performance of the trained networks by comparing the outputs. The architecture of the developed ANN model and its properties are shown in Table (3).

Table (3) Properties of the ANN Model

Architecture	9-27-27-1
Training Function	LM
Activation Function	tan sigmoid
Number of Epochs	144
Mean Squared Error	0.001

5. Results and Discussion

Table (4) represents the details of the test data used in the ANN model. The proposed ANN model was compared with the experimental test data and the author's equations.The accuracy of this model's experimental values of ultimate shear strength is shown in Fig. (2). This model predicts both the training and testing sets quite accurately with coefficients of correlation (R=0.99) and (0.93) for the training and testing data sets, respectively. Table (5) represents the details of comparison between the experimental shear strength and calculated shear strength from the ANN model and from the analytical equations (see Table 1), and the ratio of calculated and experimental shear strength. Median values for the ratio of calculated shear strength from the equations and that predicted from the ANN model for the experimental shear strength are found to be 0.99. For Vn ANN/Vn Exp, 0.37 for Vn ACI/Vn Exp, 0.52 for Vn EC/Vn Exp, 0.96 for Vn Nar/Vn Exp, 0.89 for Vn Sha/Vn Exp , and 0.55 for Vn Cld/Vn Exp. Thus, based on Table (5), the ANN values are closer to the experimental values than those of other methods.

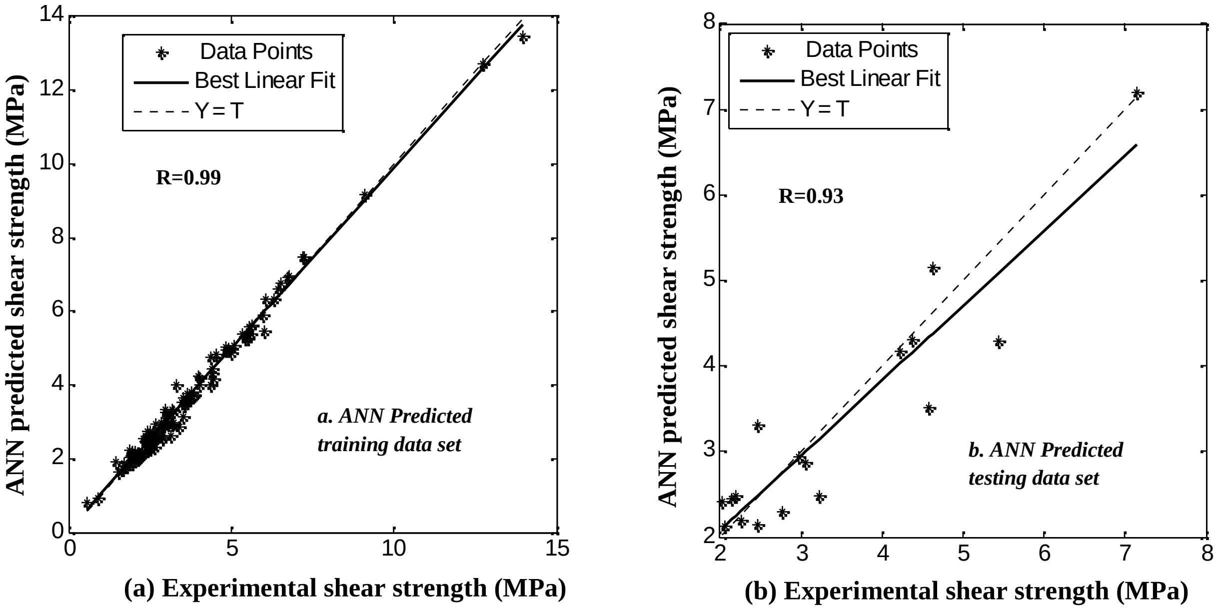

Fig.(2) Comparison of Experimental and Predicted Ultimate Shear Loads: (a) ANN Predicted Training Data Set(b) ANN Predicted Testing Data Set.

Table (4) Details of Beams Used in the Testing Sets

No.	*h (mm)*	*d (mm)*	*b (mm)*	A_s (mm^2)	*a/d*	f'_c *(MPa)*		V_f *(%)*	l_f *(mm)*	d_f *(mm)*	V_{nExp} *(MPa)*
1	254	221	152	804	2.5	36.16		1	30	0.5	2.458
2	300	280	100	560	2.5	53		0.75	30	0.5	3.22
3	200	182	100	402	2	50		1.5	30	0.5	4.23
4	200	182	100	402	3.5	48		0.75	30	0.564	2.02
5	150	135	75	158	2.5	31.4		0.75	20	0.4	2.15
6	152.4	127	101.6	402	4.4	33.21		0.22	25.4	0.25	2.461
7	152.4	127	101.6	402	4.4	33.21		0.22	25.4	0.552	2.054
8	152.4	127	101.6	402	3.4	39.71		0.88	25.4	0.552	2.971
9	375	290	50	795	2	35		0.5	30	0.5	4.58
10	150	130	85	226	3	49.4		0.25	30	0.3	2.77
11	150	130	85	226	2	49.4		0.5	39.9	0.3	4.62
12	150	128	85	402	3	57.5		1	39.9	0.3	4.37
13	150	126	85	608	2	53.6		1.5	30	0.3	7.15
14	225	197	150	603	2.8	29.9		0.75	30	0.5	2.199
15	228	204	127	570	3	22.7		1	30	0.5	3.05
16	250	215	125	760.5	4	95.4		0.5	60	0.8	2.27
17	250	212	125	402	2	68.6		0.75	50	0.8	5.44

Table (5) Comparison of Test Results

Beam No.	V_{nExp} (MPa)	V_{nANN} (MPa)	V_{nACI} (MPa)	V_{nEC} (MPa)	V_{nNar} (MPa)	V_{nSha} (MPa)	V_{nCld} (MPa)	V_{Nann}/V_{nExp}	V_{nACI}/V_{nExp}	V_{nEC}/V_{nExp}	V_{nNar}/V_{nExp}	V_{nSha}/V_{nExp}	V_{nCld}/V_{nExp}
1	2.458	3.310	1.002	1.463	2.961	2.525	1.429	1.35	0.41	0.60	1.20	1.03	0.58
2	3.22	2.49	1.213	1.572	3.010	3.057	1.331	0.77	0.38	0.49	0.93	0.95	0.41
3	4.23	4.177	1.179	1.671	3.742	3.140	1.539	0.99	0.28	0.40	0.88	0.74	0.36
4	2.02	2.411	1.155	1.648	2.366	2.674	1.527	1.19	0.57	0.82	1.17	1.32	0.76
5	2.15	2.441	0.934	1.317	2.609	2.353	1.279	1.14	0.43	0.61	1.21	1.09	0.59
6	2.461	2.141	0.960	1.458	2.088	2.101	1.859	0.87	0.39	0.59	0.85	0.85	0.76
7	2.054	2.132	0.960	1.458	2.088	2.101	1.859	1.04	0.47	0.71	1.02	1.02	0.90
8	2.971	2.938	1.050	1.547	2.517	2.450	1.926	0.99	0.35	0.52	0.85	0.82	0.65
9	4.58	3.519	0.986	1.358	5.364	2.627	2.012	0.77	0.22	0.30	1.17	0.57	0.44
10	2.77	2.297	1.171	1.664	2.599	2.820	1.620	0.83	0.42	0.60	0.94	1.02	0.58
11	4.62	5.156	1.171	1.664	3.642	3.121	1.620	1.12	0.25	0.36	0.79	0.68	0.35
12	4.37	4.315	1.264	1.751	3.085	3.042	2.254	0.99	0.29	0.40	0.71	0.70	0.52
13	7.15	7.188	1.220	1.710	5.734	3.251	2.767	1.01	0.17	0.24	0.80	0.45	0.39
14	2.199	2.484	0.911	1.408	2.535	2.232	1.308	1.13	0.41	0.64	1.15	1.01	0.59
15	3.05	2.862	0.794	1.278	2.387	1.911	1.274	0.94	0.26	0.42	0.78	0.63	0.42
16	2.27	2.195	1.628	2.036	2.605	3.647	1.899	0.97	0.72	0.90	1.15	1.61	0.84
17	5.44	4.282	1.380	1.669	3.616	3.677	1.307	0.79	0.25	0.31	0.66	0.68	0.24
Median								0.99	0.37	0.52	0.96	0.89	0.55

6. Parametric Study

One of the advantages of neural network models is that parametric studies can be easily conductedby simply varying one input parameter while all other input parameters are set to constant values. Through parametric studies, the model's performance may be verified by simulating the physical behavior of the SFRC beams through the variation of certain parameter values.

1- Effect of Shear Span-to-Depth Ratio (a/d)

Fig. (3) shows the effect of shear span-to-depth ratio (a/d) on the ultimate shear strength of SFRC beams with compressive strength. Shear strength decreases with the increase in shear span ratio. The effects become more evident with the increase in compressive strength.

When the shear span-to-depth ratio increases from 2 to 5, the shear strength decreases to 19.6% for 30 MPa compressive strength and decreases in rate (38.6%) for 90 MPa compressive strength. Fig. (3) Indicates that the SFRC beams with a small shear span-to-depth ratio appear to be more deeply affected by the compressive strength. No evident difference between shear strength is shown in the beginning especially for the shear span ratio (3, 4, and 5). However, when the compressive strength increases, the difference becomes evident, especially for 90 MPa. Compressive strength.

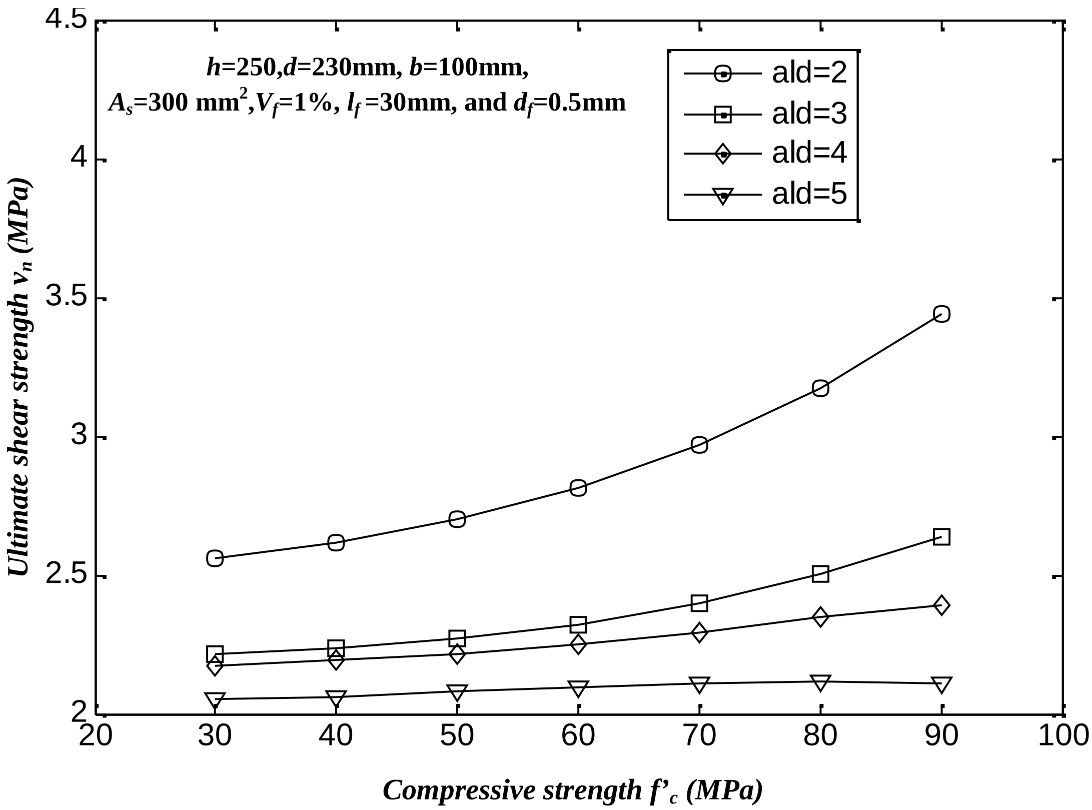

Fig. (3) Effect of a/d and Compressive Strength on the Shear Strength of FRC Beams without Stirrups.

2- Effect of Longitudinal Reinforcement (A_s)

The effect of the main reinforcement area (A_s) on the ultimate shear strength is illustrated in Fig. (4). an almost nonlinear increase appears in the shear strength of SFRC beams with the increase in main longitudinal reinforcement. For a 30 MPa compressive strength, the shear strengths are 2.36 and 2.96MPa when the A_s increases from 250mm^2 to 400mm^2, respectively. For a compressive strength of 90MPa, the shear strength is 3.19 and 3.98MPa when the A_s increases from 250mm^2 to 400mm^2, respectively.The influence of the main longitudinal reinforcement on the shear strength of SFRC beams is small and the four curves are parallel in most of its portions.

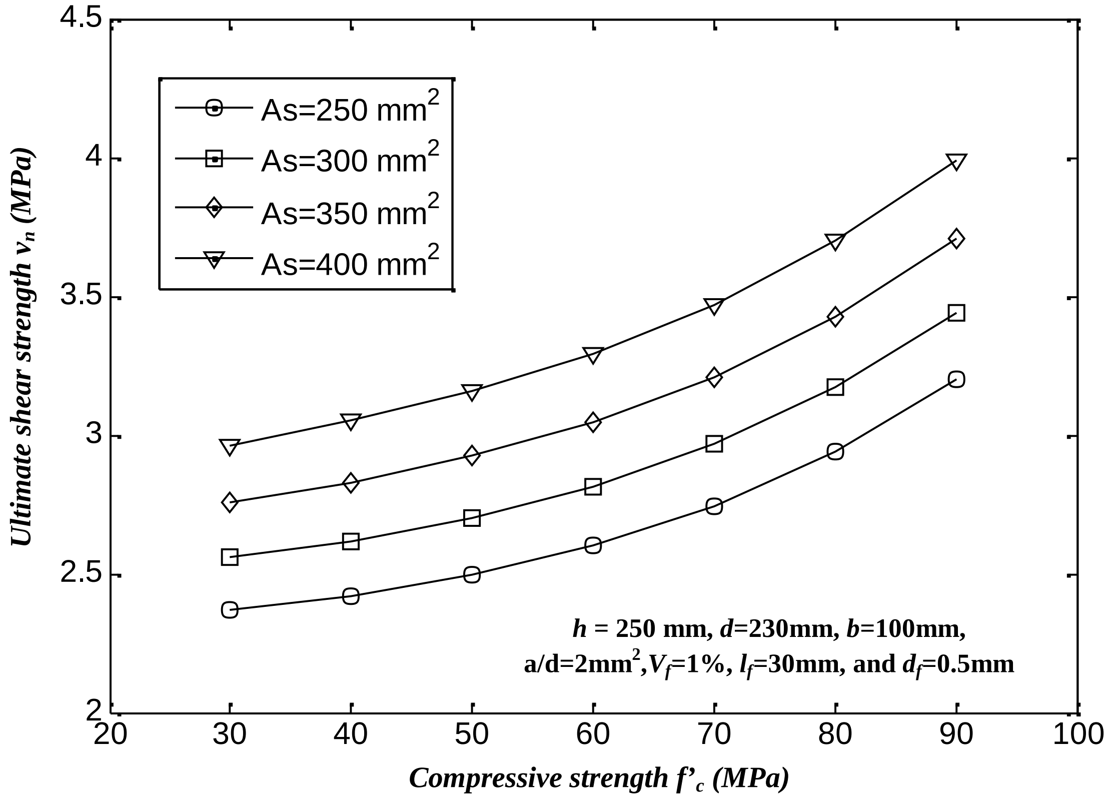

Fig. (4) Effect of A_s and Compressive Strength on the Shear Strength of FRC Beams without Stirrups.

3- Effect of Beam Height

The effect of beam height on the ultimate shear is illustrated in Fig. (5). Regardless of the other parameters, the figure shows that the nonlinear increase in ultimate shear strength of SFRC beams increases with beam height. The shear strength increases to 25.8% and 41.9% with anincrease in beam height from 200mm to 350mm, and in compressive strength from 30MPa to 90MPa, respectively. The figure also indicates a small difference in shear strength between the beam heights of 200 and 250mm. The difference becomes more evident for beam heights between 300 and 350mm.

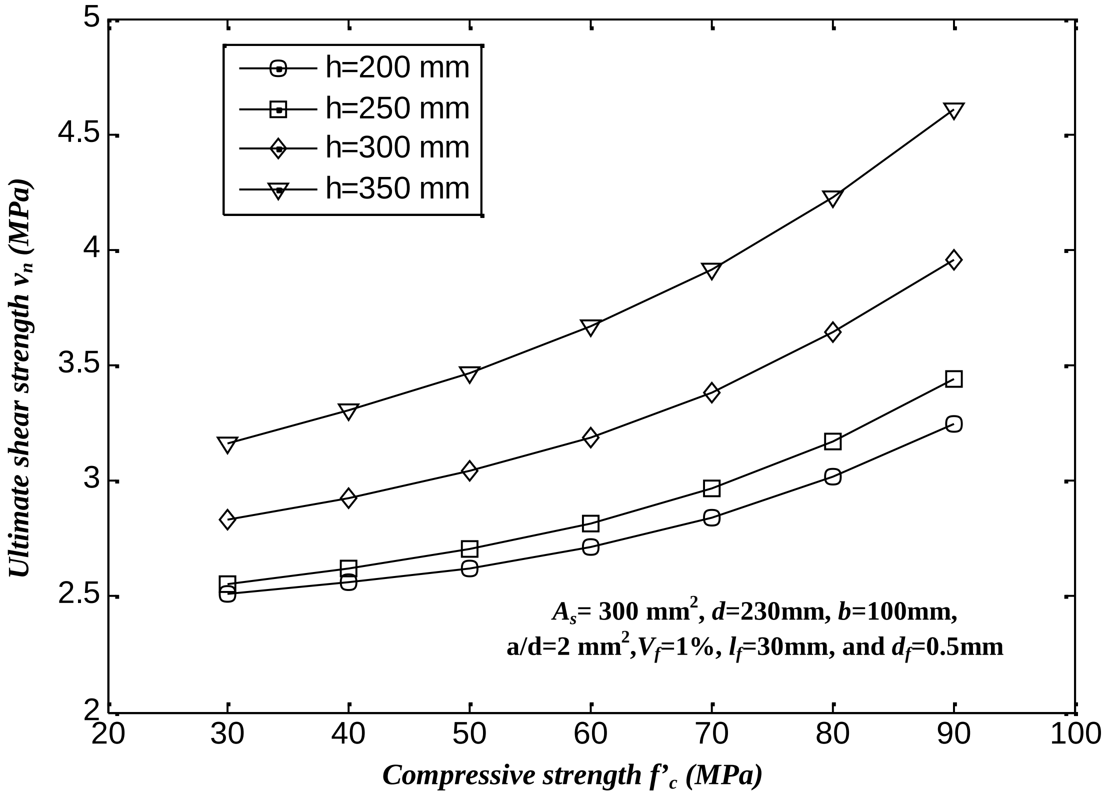

Fig. 5 Effect of Beam Height and Compressive Strength on the Shear Strength of FRC Beams without Stirrups.

4- Effect of Volume Fraction (V_f)

Fig. (6). illustrates the relationship between ultimate shear strength and compressive strength for different values of volume fraction ratio. The range of the volume fraction ratio was 0.5% to 2.0%. When the other parameters are kept constant, as shown Fig. (6) the shear strength increases with the increase in volume fraction ratio. For compressive strength of 30 MPa. the difference between shear strength values is evident for different values of V_f, but the increase in compressive strength decreases the difference between shear strength values, especially for a compressive strength of 90MPa and 1%, 1.5%, and 2% volume fraction ratio. Thus, the shear strength increases to 51.2% and 26.3% when the volume fraction ratio increases from 0.5% to 2% for a compressive strength of 30 and 90 MPa, respectively.

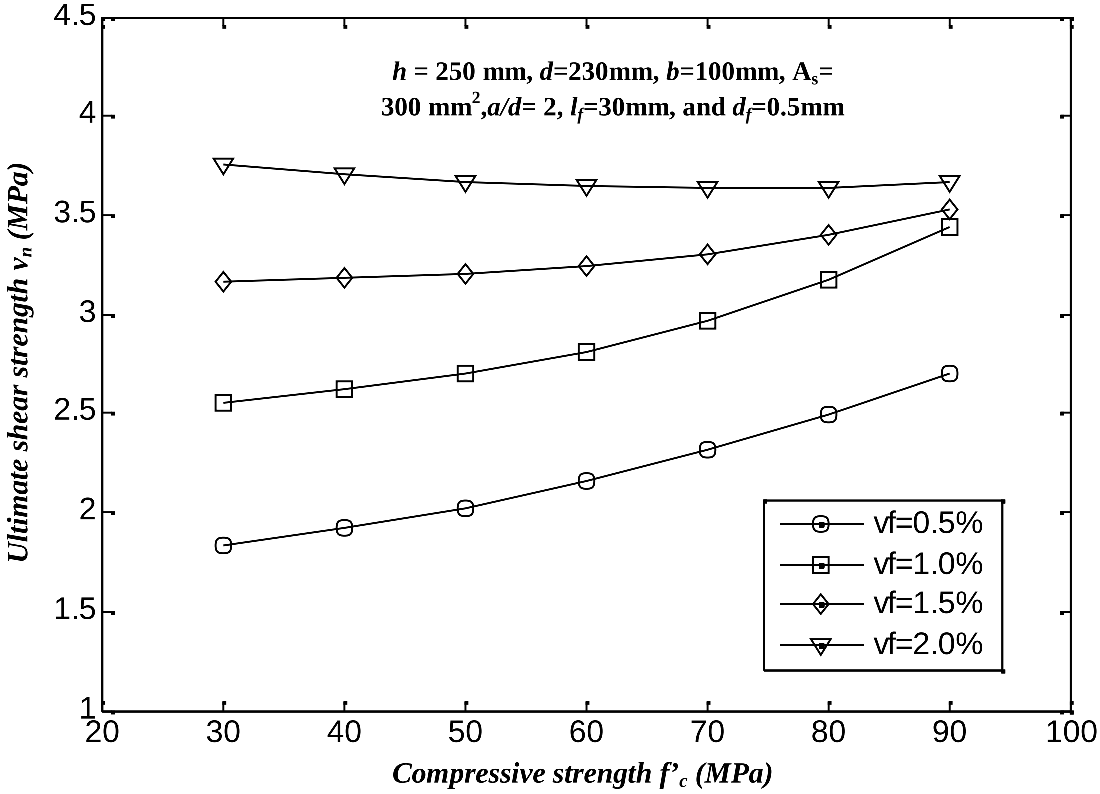

Fig. (6) Effect of V_f and Compressive Strength on the Shear Strength of FRC Beams without Stirrups.

5- Effect of Fiber Length (lf)

The effect of lf on the shear strength of SFRC beams is shown in Fig.(7). The ultimate shear strength of SFRC beams increased with the increase in lf. This phenomenon is true for all compressive strengths. For a compressive strength of 30MPa, the percentage increase in ultimate shear strength is 28%when the lf increases in lf from 20mm to 50mm. For a compressive strength of 90MPa, the ultimate shear strength increases to 49.1% when the lf increases from 20mm to 50mm.

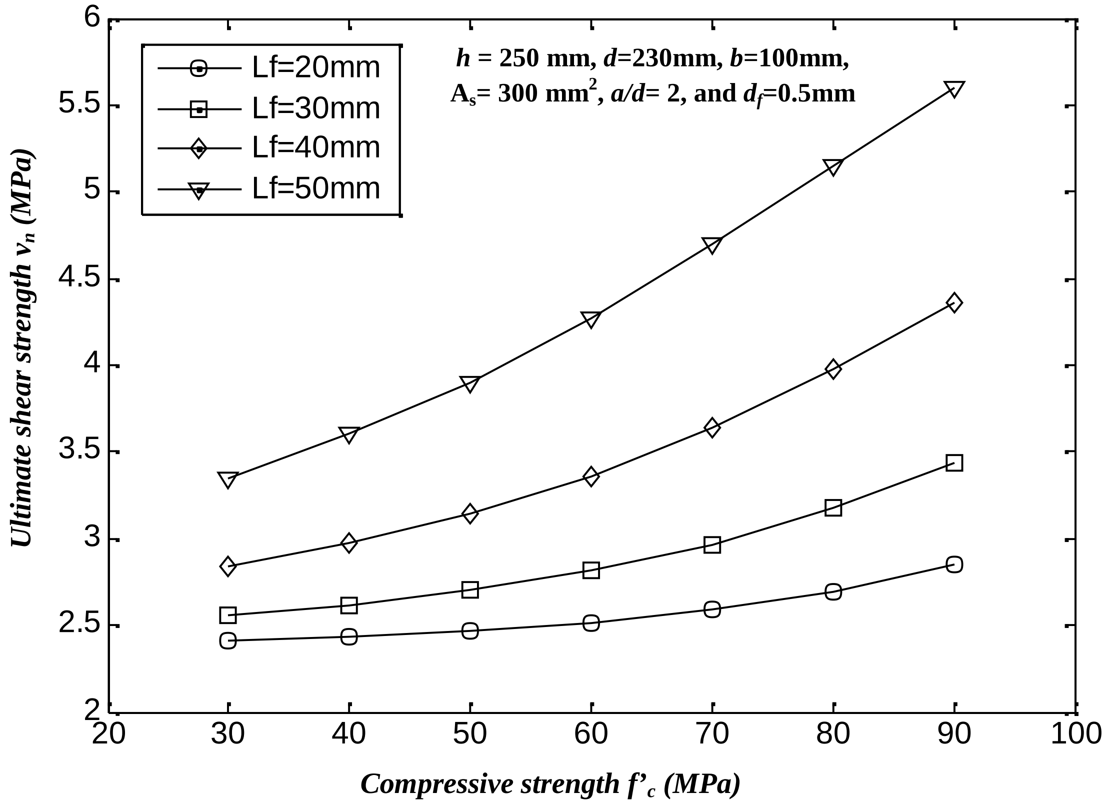

Fig. (7) Effect of l_f and Compressive Strength on the Shear Strength of FRC Beams without Stirrups.

Conclusions

In this study, the ANN model was developed to simulate the behavior of SFRC beams without web reinforcement using a BPNN. The measured experimental values were compared with the shear strength calculated from the ANN model and that of the theoretical existing formula. A parametric study was carried out to explain the effects of various parameters on the behavior of SFRC beams without web reinforcement.The following conclusions were drawn from this study:

- The ANN model is stronger and valid for simulating the behavior of SFRC beams without web reinforcement. The ANN predictions are accurate, provided the input data are within the ranges used for training the network.
- The ANN algorithm is an effective and inexpensive tool for carrying out a parametric study among several parameters that affect the physical phenomenon in engineering, as demonstrated inthe case of the ultimate shear strength of SFRC beams without web reinforcement.
- Based on the parametric study, the shear span, compressive strength of concrete, volume fraction, and fiber length are the major factors affecting the behavior of SFRC beams without web reinforcement.

Notations

a	Shear span length, *mm*
b	Beam width, *mm*
d	Effective depth of beam, *mm*
d_f	Diameter of fiber
f'_c	Cylindrical concrete compressive strength, *MPa*
F	Fiber factor
h	Overall depth of corbel, *mm*
l_f	Fiber length
V_f	Volume fraction ratio (%)
v_n	Shear strength, *MPa*
V_nExp	Experimental shear strength, *MPa*
$V_n\ ANN$	Shear strength according to the ANN model, *MPa*
$V_n\ ACI$	Shear strength according to the ACI318-08 model, *MPa*
$V_n\ EC$	Shear strength according to the Euro code EC-2 model, *MPa*
V_nCld	Shear strength according to the Clade-04 model, *MPa*
V_nNar	Shear strength according to the Narayanan model, *MPa*
V_nSha	Shear strength according to the Sharma model, *MPa*
ρ	Longitudinal reinforcement ratio, A_s/bd
a/d	Shear span-to-effective depth ratio

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