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An artificial neural network approach for prediction of long-term strength properties of steel fiber reinforced concrete containing fly ash

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Abstract: In this study, an artificial neural network (ANN) model for studying the strength properties of steel fiber reinforced concrete (SFRC) containing fly ash was devised. The mixtures were prepared with 0 wt%, 15 wt%, and 30 wt% of fly ash, at 0 vol.%, 0.5 vol.%, 1.0 vol.% and 1.5 vol.% of fiber, respectively. After being cured under the standard conditions for 7, 28, 90 and 365 d, the specimens of each mixture were tested to determine the corresponding compressive and flexural strengths. The parameters such as the amounts of cement, fly ash replacement, sand, gravel, steel fiber, and the age of samples were selected as input variables, while the compressive and flexural strengths of the concrete were chosen as the output variables. The back propagation learning algorithm with three different variants, namely the Levenberg-Marquardt (LM), scaled conjugate gradient (SCG) and Fletcher-Powell conjugate gradient (CGF) algorithms were used in the network so that the best approach can be found. The results obtained from the model and the experiments were compared, and it was found that the suitable algorithm is the LM algorithm. Furthermore, the analysis of variance (ANOVA) method was used to determine how importantly the experimental parameters affect the strength of these mixtures.

Key words:Fly ash, Steel fiber, Strength properties, Artificial neural network (ANN), Analysis of variance (ANOVA) methoddoi:10.1631/jzus.A0720136Document code: ACLC number: TU5

INTRODUCTION

It has been found that incorporating steel fibers in concrete improves its mechanical properties, including flexural and splitting tensile strength and ductility, toughness, cracking and abrasion resistance. For achieving longer life and higher strength, toughness and stress resistance, steel fiber reinforced concrete (SFRC) is now being widely used in structures such as flooring, housing, precasting, tunnelling, heavy duty pavement and mining. The characteristic and performance of SFRC depend on the properties of fibers used, such as density, geometry, orientation, distribution and types.

There are many extensive studies carried out to

evaluate the edition of steel fiber on the hardened properties of concrete (Banthia and Mani, 1993; Mindess *et al.*, 1994; Ling and Jiang, 1994; Huang and Zhao, 1995; Khaloo and Kim, 1996; Gao *et al.*, 1997; Eren and Celik, 1997; Taylor *et al.*, 1997; Lok and Pei, 1998; Nataraja *et al.*, 1999; Ding and Kusterle, 2000; Song and Hwang, 2004; Beddar *et al.*, 2004; Kumar *et al.*, 2005; Altun *et al.*, 2007; Topcu and Canbaz, 2007; Yazıcı *et al.*, 2007).

Recently, artificial neural network (ANN) modelling of concrete properties has been studied by many investigators. Fazel Zarandi *et al.*(2008) presented a fuzzy polynomial neural networks model for prediction of the compressive strength of concrete. Topcu and Saridemir (2007; 2008a; 2008b) presented an ANN model for prediction of strength properties of concrete. Yeh (2007) presented an ANN model and

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second-order regressions for prediction of slump flow of concrete. Demir (2008) presented an ANN model for prediction of elastic modulus of concrete. Altun et al.(2008) presented an ANN model for compressive strength of lightweight concrete containing steel fiber, but did not cover the topic on the long-term strength properties (compressive strength and flexural strength) of concrete containing fly ash and steel fiber. Because of this, an ANN model with three different learning algorithms, namely the Levenberg-Marquardt (LM), scaled conjugate gradient (SCG) and Fletcher-Powell conjugaten gradient (CGF) algorithms, has been devised to predict the strength properties of concrete containing fly ash and steel fiber. Furthermore, the effect of the experimental parameters on strength properties was evaluated statistically and the level of significance of the parameters affecting strength properties was determined by using analysis of variance (ANOVA) method.

EXPERIMENTAL PROGRAM

Properties of materials used

1. Cement

The Portland cement CEM I 42.5 R with a specific gravity of 3.16 g/cm^3 was used in this study. Its initial and final setting time was 138 h and 203 h, respectively. The Blaine specific surface area was $3250 \text{ cm}^2/\text{g}$. Its chemical compositions are shown in Table 1.

Table 1	Chemical compositi	on of ce	ment (wt%)
Orrida	Weight content	Orida	Waight cont

Oxide	Weight content	Oxide	Weight content
SiO ₂	19.71	SO_3	2.72
Al_2O_3	5.20	K_2O	0.90
Fe ₂ O ₃	3.73	Na ₂ O	0.25
CaO	62.91	MgO	2.54
Loss on ignition	0.96		

2. Fly ash

Fly ash used was obtained from a new built Sugozu power station located in southern Turkey. Its chemical composition is presented in Table 2 together with the standard specifications. According to ASTM C-618 (1998) standard this fly ash can be classified as Class F fly ash. Specific gravity and Blaine specific surface area of this ash are found to be 2.31 and 2900 cm^2/g , respectively. It can be seen from Table 2 that this fly ash satisfies the requirement of both ASTM C-618 (1998) and TS EN 450 (1998) standards.

 Table 2 Limits of standards for chemical composition of fly ash (wt%)

Chamical composition	Elv och	Standard		
Chemical composition	FTY ash	ASTM C-618	TS EN 450	
SiO ₂	52.50		_	
Al_2O_3	22.82	—	_	
Fe ₂ O ₃	5.34	—	_	
SiO ₂ +Al ₂ O ₃ +Fe ₂ O ₃	80.66	70.0 min		
Cao	7.16	—	_	
MgO	2.56	5.0 max	—	
Cl	0.003	—	0.1 max	
Free CaO	0.10	—	1.0 max	
K ₂ O	0.99	—	—	
Na ₂ O	0.48	1.5 max	—	
SO ₃	0.20	5.0 max	3.0 max	
Loss on ignition	3.35	6.0 max	5.0 max	
Moisture	0.07	3.0 max	_	

3. Aggregate and its grading

Dry and clean natural river aggregate was used in concrete mixture. The gravel was 16 mm maximum nominal size with 1.1% absorption value and its relative density at saturated surface dry (SSD) condition was 2.70. The absorption value of the sand used was 1.2% and its relative density at SSD condition was 2.61. The grading of the mixed aggregate is presented in Table 3.

Table 3 Mixed aggregate gradation

Particle size	Weight content	Particle size	Weight content
(mm)	(wt%)	(mm)	(wt%)
0~0.25	3.5	2~4	18.5
0.25~0.50	11.2	4~8	31.1
0.5~1.0	5.2	8~16	23.4
1~2	7.1		

4. Fiber

An RC 65/35 BN type low carbon steel with both ends hooked was used as fiber. The steel fibers have length of 35 mm, diameter of 0.55 mm, aspect ratio of 64, and density of 7.85 g/cm^3 .

5. Plasticizer

A commercial carboxylic type hyperplasticizer was used to maintain the workability of fresh concrete. The dosage of hyper plasticizer was kept constant at 1% by mass of the binder content of concrete.

Mixture composition

Table 4 shows the detailed test variables, in which four levels exist. Approximate concrete compositions are given in Table 5 in the unit of per cubic meter. Mixture design is made using absolute volume method. At the beginning of the mixture design, binder content of 400 kg/m³ and water-cement ratio of 0.35 were chosen as constant parameters, then, the volume of aggregate was determined for the control Portland cement concrete by assuming approximately 2% (v/v) air is entrapped in fresh concrete. The volume of aggregate was used to determine the aggregate weight. Fresh fiber reinforced concretes containing 0 vol.%, 0.5 vol.%, 1.0 vol.% and 1.5 vol.% steel fiber by volume of concrete basis were prepared containing 0 wt%, 15 wt% and 30 wt% fly ash as cement replacement on mass basis, respectively. Aggregate weight in the cubic meter was adjusted when fly ash or fiber was introduced into concrete.

Table 4Levels of the variables for compressive andflexural strength

Level	Time $T(d)$	Steel fiber S (vol.%)	Fly ash F (wt%)
1	7	0	0
2	28	0.5	15
3	90	1	30
4	365	1.5	_

Table 5	Concrete	compositions	for a	cubic r	meter
I and to to	Concrete	compositions	101	cubic i	motor

No.	Cement (kg/m ³)	Fly ash (kg/m ³)	Water (L/m ³)	Plasti- cizer (kg/m ³)	Sand (kg/m ³)	Gravel (kg/m ³)	Stell fiber (kg/m ³)
A1	400	0	140	4	756	1.135	0
A2	400	0	140	4	751	1.127	39.25
A3	400	0	140	4	746	1.119	78.50
A4	400	0	140	4	740	1.111	117.75
B1	340	60	140	4	750	1.124	0
B2	340	60	140	4	744	1.116	39.25
В3	340	60	140	4	739	1.108	78.50
B4	340	60	140	4	734	1.100	117.75
C1	280	120	140	4	742	1.114	0
C2	280	120	140	4	737	1.106	39.25
C3	280	120	140	4	732	1.097	78.50
C4	280	120	140	4	726	1.090	117.75

Preparation and testing of specimens

The procedure for mixing the fiber-reinforced concrete is as follows. First, the gravel and sand were

placed in a concrete mixer and dry-mixed for 1 min. Second, the cement, fly ash and fiber were spread and dry-mixed for 1 min. Third, the mixing water (90 vol.%) was slowly added in and mixed for 2 min. Fourth, the remaining mixing water (10 vol.%) and plasticizer were added in and mixed for 3 min. Last, the freshly mixed fiber-reinforced fly ash concrete was cast into 150 mm cubes and 100 mm×100 mm×500 mm beams separately for later compressive strength and flexural tensile strength tests, respectively. After casting, each of the specimens was allowed to stand for 24 h in the laboratory before demolding. Demoulded specimens were stored in water at (23 ± 2) °C until testing days.

Compressive and flexural strength was measured up to 365 d of testing. All the specimens were tested by using per Turkish Standard Specifications for testing hardened concrete TS-EN 12390-1,2,3,4,5 (2002; 2002; 2003; 2002; 2002).

STATISTICAL ANALYSIS OF EXPERIMENTAL RESULTS

In this study, ANOVA and *F*-test were performed to evaluate statistically the major process parameters and their contributions to the strength of the SFRC containing fly ash. F_{A_0} is *F*-test for variance comparison. Statistically, there is a tool which provides a decision at some confidence level as to whether these estimates are significantly different. This tool is called an *F*-test. When *F*-value becomes large enough, the two sample variances are accepted as being unequal at some confidence level. *F*-tables which list the required *F*-ratios to achieve some confidence level are provided in the appendixes (Ross, 1996; Liao *et al.*, 1997; Lin *et al.*, 2000).

In the ANOVA, a loss function is used to calculate the deviation between the experimental value and the desired value. Some characteristics, such as bond strength, compressive strength and splitting tensile strength, are not negative and are called the larger-the better type quality characteristics. The larger characteristics indicate a better performance (compressive and flexural strength), as far as the strength properties of SFRC containing fly ash are concerned. Therefore, the "larger is better (LB)" loss function for strength properties was selected to obtain the optimal conditions (Eq.(1)). The loss function L_{ij} of LB performance characteristic can be expressed as

$$L_{ij} = \frac{1}{n} \sum_{k=1}^{n} \frac{1}{y_{ijk}^2},$$
 (1)

where L_{ij} is the loss function of the *i*th performance characteristic in the *j*th experiment, *n* the number of tests, and y_{ijk} the experimental value of the *i*th performance characteristics in the *j*th experiment at the *k*th test.

The loss function is further transformed into a signal-to-noise (S/N) ratio for determining the performance characteristic deviating from the desired value. The S/N ratio n_{ij} for the *i*th performance characteristic in the *j*th experiment can be expressed as

$$n_{ij} = -10 \lg L_{ij}.$$
 (2)

The control factors and the levels given in Table 4 were used for calculating the S/N ratio. The S/N ratios of the strength properties of SFRC containing fly ash were calculated for each level of the experimental parameters. Furthermore, the ANOVA and F-test values were calculated.

Compressive strength

Compressive strength of concrete mixture was measured at the ages of 7, 28, 90 and 365 d. The results are presented in Table 6. The compressive strength listed on the table shows no obvious evidence of any optimum fiber content for concrete existing. In the 0.5 vol.%, 1.0 vol.% and 1.5 vol.% fiber content groups, there is a slight increase of compressive strength with addition of steel fiber at 7, 28, 90 and 365 d. The addition of steel fibers into the concrete mixture did not significantly improve its ultimate compressive strength, but only a small increase was observed in both short- and long-term curing time.

Based on the S/N ratio, the maximum

compressive strength was obtained at 365 d, for the 1.5 vol.% of steel fiber and 0 wt% of fly ash admixture (Table 7). The results of ANOVA for the compressive strength properties of SFRC containing fly ash are presented in Table 8.

As shown in Table 8, the compressive strength properties of SFRC containing fly ash have obtained higher F_{A_0} values. The analysis indicated that the experimental error was very low at a level of 3.30%. Table 8 shows the relative importance of the experimental parameters used in this study on the compressive strength properties of SFRC containing fly ash, and that the time has an utmost importance on compressive strength.

Table 6 Compressive strength results

Mixture	Fly ash	Steel	Compressive strength (MPa)			
No.	F (wt%)	(vol.%)	7 d	28 d	90 d	365 d
A1	0	0	64.4	77.1	86.5	102.8
A2	0	0.5	65.5	78.2	84.4	100.9
A3	0	1.0	63.0	80.5	88.2	96.4
A4	0	1.5	66.7	81.0	89.3	97.7
B1	15	0	55.1	67.8	80.2	94.5
B2	15	0.5	55.4	68.3	78.2	94.2
B3	15	1.0	54.6	71.7	81.2	94.5
B4	15	1.5	58.7	72.7	83.1	98.5
C1	30	0	51.0	63.6	77.6	93.4
C2	30	0.5	52.1	64.4	81.5	95.5
C3	30	1.0	53.3	65.0	79.6	95.5
C4	30	1.5	53.6	60.7	78.5	93.4

Table 7 S/N ratio of compressive strength^{*}

Level	Ν	fean S/N ratio ((dB)
1	35.20	37.45	38.24**
2	36.98	37.50	37.40
3	38.31	37.55	36.98
4	39.68**	37.66**	_

Time *T*: 365 d; Steel fiber *S*: 1.5 vol.%; Fly ash *F*: 0 wt%; *Overall mean S/N ratio=37.540418 dB; ** Optimum level

Degrees of freedom (<i>f</i>)	Sum of square (SS_A)	Variance (V_A)	$F_{ m A_0}$	Contribution (%)			
3	131.64	43.88	345.17*	87.74			
3	0.29	0.10	0.75	0.19			
2	13.15	6.58	51.72*	8.77			
39	4.96	0.13	—	3.30			
47	150.04	—		100			
	Degrees of freedom (<i>f</i>) 3 3 2 39 47	Degrees of freedom (f) Sum of square (SS _A) 3 131.64 3 0.29 2 13.15 39 4.96 47 150.04	Degrees of freedom (f) Sum of square (SS _A) Variance (V_A) 3 131.64 43.88 3 0.29 0.10 2 13.15 6.58 39 4.96 0.13 47 150.04 —	Degrees of freedom (f) Sum of square (SS _A) Variance (V _A) F_{A_0} 3 131.64 43.88 345.17* 3 0.29 0.10 0.75 2 13.15 6.58 51.72* 39 4.96 0.13 — 47 150.04 — —			

Table 8 Results of ANOVA for compressive strength

* At least 99% confidence

Flexural strength

The flexural strength data, obtained by testing a 100 mm×100 mm×500 mm prism specimen according to the relevant standards TS 10515 (1992), are given in Table 9.

				-		
Mixture	Fly ash	Steel	Flexural strength (MPa)			MPa)
No.	<i>F</i> (wt%)	tiber S (vol.%)	7 d	28 d	90 d	365 d
A1	0	0	7.61	7.82	8.01	8.28
A2	0	0.5	7.65	7.37	7.89	8.04
A3	0	1.0	8.18	8.24	8.77	8.95
A4	0	1.5	9.86	10.14	11.47	12.05
B1	15	0	6.28	6.71	7.67	7.95
B2	15	0.5	6.63	6.96	7.50	7.72
В3	15	1.0	6.39	7.62	7.75	7.98
B4	15	1.5	8.16	9.07	10.08	11.96
C1	30	0	4.85	5.89	6.27	6.98
C2	30	0.5	5.24	6.53	6.57	6.89
C3	30	1.0	5.51	6.45	7.20	7.66
C4	30	1.5	6.35	8.69	9.48	11.58

 Table 9 Flexural strength results

Steel fibers have no effects on flexural strength at 0.5 vol.% used in this study. However, the improvement started from 0%~15% at 1.0 vol.% and expanded to 30%~66% increment at 1.5 vol.%. These increments were found to be significant.

The increase in flexural tensile strength of concrete with the addition of steel fiber was explained as follows. Under the fourth point loading, the concrete prism specimen was subjected to bending, which results in tensile and compressive stresses depending on the position of distance from neutral axis. At the failure load, resultant compressive stress is nearly 6%~10% of the compressive strength of the material. Therefore, compressive strength does not play an important role in the flexural failure. However, it is the flexural tensile stress and strength that play an important role in the failure of the beam. The tensile stress causes cracking in the beam, and consequently results in failure. Randomly distributed steel fibers arrest these cracks and stitch them. Therefore, when steel fibers arrest these cracks, the load to fail the beam specimen has to be increased. Thus, steel fiber addition increases the ultimate flexural strength of the material. Based on the S/N ratio, the maximum flexural strength was obtained at 365 d, 1.5 vol.% steel fiber and 0 wt% fly ash admixture (Table 10). The results of ANOVA for the flexural strength properties of SFRC containing fly ash are presented in Table 11.

Table 10 S/N ratio of flexural strength^{*}

Level	М	ean S/N ratio	(dB)
1	16.60	16.84	18.77**
2	17.54	16.95	17.83
3	18.17	17.49	16.70
4	18.75**	19.79**	

Time *T*: 365 d; Steel fiber *S*: 1.5 vol.%; Fly ash *F*: 0 wt%; * Overall mean S/N ratio=37.540418 dB; ** Optimum level

As shown in Table 11, the flexural strength properties of SFRC containing fly ash are obtained with higher F_{A_0} values. The analysis indicated that the experimental error was at a low level (8.99%). Table 11 shows the relative importance of the experimental parameters used in this study on the flexural strength properties of SFRC containing fly ash, and that the steel fiber has an utmost importance on flexural strength.

MODELLING OF EXPERIMENTAL RESULTS

Multilpe linear-nonlinear regression analysis of experimental results

Multiple linear-nonlinear regression is a method used to model the linear and nonlinear relationship between a dependent variable and one or more independent variables. When there are *i* independent variables $x_1, x_2, ..., x_i$, the linear multiple regression equation is in the general form of

Table 11 Results of ANO VA for nexular strength								
Control factor	Degrees of freedom (f)	Sum of square (SS_A)	Variance (V_A)	$F_{\mathrm{A}_{0}}$	Contribution (%)			
Time T	3	30.82	10.27	30.41*	21.03			
Steel fiber S	3	68.31	22.77	67.41*	46.62			
Fly ash F	2	34.22	17.11	50.65^{*}	23.35			
Error	39	13.17	0.34	_	9			
Total	47	146.52	—		100			

Table 11 Results of ANOVA for flexural strength

*At least 99% confidence

$$y = a_0 + a_1 x_1 + a_2 x_2 + \dots + a_i x_i.$$
(3)

The nonlinear multiple regression equations are in the general form as

$$y = a_0 + a_1 \ln x_1 + a_2 x_2 + a_3 x_3 + \dots + a_i x_i, \qquad (4)$$

$$y = \exp(a_0 + a_1 x_1 + a_2 x_2 + \dots + a_i x_i),$$
(5)

where y is the dependent variable, $x_1, x_2, ..., x_i$ are the independent variables (explanatory variables) and *a* denotes coefficient vector.

In this study, multiple linear-nonlinear regression analysis was carried out to determine the relations between the dependent variable of compressive or flexural strength (y) and the independent variables, i.e., cement (x_1), fly ash (x_2), sand (x_3), gravel (x_4), steel fiber (x_5) and days (x_6). All samples were used for multiple linear regression analyses. Multiple linear-nonlinear regression results are presented in Tables 12 and 13.

It can be seen from Tables 12 and 13 that the difference between linear and nonlinear regression models is small. Furthermore, the low correlation coefficient (between 0.80 and 0.72) obtained from multiple regression analysis indicated the suitability of the used relation (power function) and the correctness of the calculated constants.

ANN model for prediction of experimental results

ANNs are biologically inspired and mimic the human brain. They consist of a large number of simple processing elements called as neurons. A schematic diagram for an artificial neuron model is given in Fig.1.

Let $X=(X_1, X_2, ..., X_n)$ represent the *n* inputs applied to the neuron, where W_j represents the weight for input X_j and *b* is a bias, then the output of the neuron is given by Eq.(6). These neurons are connected with connection links. Each link has a weight that is multiplied by transmitted signal in network. Each neuron has an activation function to

determine the output. There are many kinds of activation functions. Usually nonlinear activation functions such as *sigmoid*, *step* are used. ANNs are trained by experience, when an unknown input is applied to the network, it can generalize from past experiences and produce a new result (Haykin, 1994; Hanbay *et al.*, 2008a; 2008b).

$$u = \sum_{j=0}^{n} X_{j}W_{j} - b$$
, and $V = f(u)$. (6)

ANNs are systems that are deliberately constructed to make use of some organizational principles resembling those of the human brain (Haykin, 1994; Hanbay *et al.*, 2008a; 2008b). They represent the new promising generation of information processing systems.

When designing an ANN model, a number of considerations must be taken into account. First of all the suitable structure of the ANN model must be chosen. After this the activation function and the activation values need to be determined. The number of layers and units in each layer must be chosen. Generally desired model consists of a number of layers. The most general model assumes complete interconnections between all units. These connections

Table 12 Multiple linear regression results

Equation	a_0	a_1	a_2	a_3	a_4	a_5	a_6	R^2
Compressive strength (Eq.(3))	-337.8	0.02	0	0.54	0.71	0.09	0.09	0.78
Flexural strength (Eq.(3))	¹ –437	-0.06	50	-0.18	0.53	0.11	0.004	0.74



Fig.1 Artificial neuron model

Table 13	Multiple r	nonlinear	regression	results

			-	U				
Equation	a_0	a_1	a_2	<i>a</i> ₃	a_4	a_5	a_6	R^2
Compressive strength (Eq.(4))	-16.47	-7.02	-0.09	0.08	0.17	0.04	0.09	0.80
Flexural strength (Eq.(4))	-1.89	1.36	-0.01	0.0008	0.000002	0.02	0.004	0.72
Compressive strength (Eq.(5))	-0.15	0.01	0.01	-0.0003	0.0000000009	0.0001	0.001	0.77
Flexural strength (Eq.(5))	-0.26	0.006	0.004	-0.0002	0.0000003	0.003	0.0005	0.75

can be bidirectional or unidirectional. ANN can create its own organization or representation of the information it receives during learning time (Haykin, 1994; Hanbay *et al.*, 2008a; 2008b). There are many kinds of ANN structures. One of these is multilayer feedforward ANN as shown in Fig.2.



Fig.2 Multilayer feed forward neural network structure

In this study, it is proposed to network models by means of six input and two output parameters. The parameters such as amount of cement, fly ash replacement, sand aggregate, gravel aggregate, steel fiber, and age of samples were selected as input variables. The model output variables were the compressive and flexural strength of the concrete. The data were normalized by dividing by max values. The back propagation learning algorithm has been used in a feed-forward, single hidden layer neural network. ANN architecture used for this study is given in Fig.3 (Avcı, 2007; 2008).



The variants of the algorithm used in the study are the Levenberg-Marquardt (LM), scaled conjugate gradient (SCG) and Fletcher-Powell conjugate gradient (CGF) algorithms. The computer program was performed under MATLAB software using the neural network toolbox. In the training, the number of neurons on the hidden layer is 5. A dataset including 48 data samples obtained from experimental studies were used for ANNs. From these, 24 data patterns were used for training the network, and the remaining 24 patterns were randomly selected and used as the test dataset. The results are shown in Figs.4~6.

Figs.4 and 5 present the measured strengths vs predicted strengths by the ANN model with R^2 coefficients. It can be seen from Figs.4a and 5a that the ANN model predicts the compressive and flexural strength of the SFRC containing fly ash with R^2 of 0.96 and 0.84, respectively. However, Figs.4b, 5b, 4c and 5c show that the ANN model predicts the compressive and flexural strength of the SFRC containing fly ash with R^2 of 0.75, 0.75, 0.93 and 0.75, respectively. The training performance during the training process is given in Fig.6 showing that the SCG and the CGF algorithms are not completely learning but the LM algorithm is the best learning algorithm for this study. The obtained results in this study are similar to those of Altun *et al.*(2008).

CONCLUSION

In this study, an ANN model for the strength properties of the SFRC containing fly ash was devised. By comparing laboratory and computer work, the following conclusions can be drawn.

The addition of steel fibers into concrete mixture did not significantly improve its ultimate compressive strength. Based on the S/N ratio, the optimum parameters for the compressive strength was obtained at 365 d, 1.5 vol.% steel fiber and 0 wt% fly ash admixture. Based on ANOVA and *F*-test, it was found that the most effective parameters on the compressive strength were (in descending order) time, fly ash percentage and steel fiber percentage.

Steel fibers have no effects on flexural strength at 0.5 vol.% in this study. However, an improvement of $0\sim15\%$ was observed at 1.0 vol.% and expanded to $30\%\sim66\%$ at 1.5 vol.%. Based on the S/N ratio, the optimum parameters for the flexural strength was obtained at 365 d, 1.5 vol.% steel fiber and 0 wt% fly ash admixture. Based on ANOVA and *F*-test, it was



Fig.4 Linear relationship between measured and predicted compressive strengths. (a) LM algorithm; (b) SCG algorithm; (c) CGF algorithm



Fig.5 Linear relationship between measured and predicted flexural strength. (a) LM algorithm; (b) SCG algorithm; (c) CGF algorithm



Fig.6 Training performance. (a) LM algorithm; (b) SCG algorithm; (c) CGF algorithm

found that the most effective (in a descending order) parameters on the flexural strength were steel fiber, fly ash percentage and time.

Correlation coefficients obtained from multiple linear-nonlinear regression analysis for compressive strength are 0.78, 0.80, and 0.77, respectively, while those for flexural strength are 0.74, 0.72, and 0.75, respectively.

Three ANN algorithms were tested for this

study. The LM algorithm is the best learning algorithm for this study. Furthermore, the comparison of the results obtained with ANN and with multiple linear-nonlinear regression shows that ANN is more useful than multiple linear-nonlinear regression models because it operates more rapidly and easily with higher correlation coefficients. Therefore, ANN can be used to predict the strength properties of SFRC containing fly ash either in the long- or short-term.

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