

Estimation of compression strength of polypropylene fibre reinforced concrete using artificial neural networks

R. Tuğrul Erdem¹, Erkan Kantar¹, Engin Gücüyen¹ and Özgür anil^{*2}

¹Civil Engineering Department, Celal Bayar University, Manisa, Türkiye

²Civil Engineering Department, Gazi University, Ankara, Türkiye

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Abstract. In this study, Artificial Neural Networks (ANN) analysis is used to predict the compression strength of polypropylene fibre mixed concrete. Polypropylene fibre admixture increases the compression strength of concrete to a certain extent according to mix proportion. This proportion and homogenous distribution are important parameters on compression strength. Determination of compression strength of fibre mixed concrete is significant due to the veridicality of capacity calculations. Plenty of experiments shall be completed to state the compression strength of concrete which have different fibre admixture. In each case, it is known that performing the laboratory experiments is costly and time-consuming. Therefore, ANN analysis is used to predict the 7 and 28 days of compression strength values. For this purpose, 156 test specimens are produced that have 26 different types of fibre admixture. While the results of 120 specimens are used for training process, 36 of them are separated for test process in ANN analysis to determine the validity of experimental results. Finally, it is seen that ANN analysis predicts the compression strength of concrete successfully.

Keywords: compression strength; polypropylene fibre; artificial neural networks

1. Introduction

Concrete is a widely used building material in the world. It is easy to access the raw material of concrete. Also, concrete is shapeable, economic and it is possible to arrange the compound of concrete. Compression strength of the hardened concrete is the most important property that describes its quality and suitability for construction works. Also, it considers the mother strength, where most of other properties and strengths; such as tension, flexural, shear and bond with steel reinforcement are improved with the improvement in compression strength and vice versa. Most often, an ultimate target in the mixture design is the 28-day compression strength. This strength is usually determined based on a standard uni-axial compression test, and is accepted universally as a general index of concrete strength (Siddique *et al.* 2011).

Polypropylene fibre admixture is commonly used in fabrication of concrete and reinforced concrete members. This admixture increases the compression strength of concrete somewhat and also increases the ductility value which is very important. Whereas compression strength of

*Corresponding author, Associate Professor, E-mail: oanil@gazi.edu.tr

concrete increases, deformation capability of it and ductility is affected negatively and concrete is getting brittle unfortunately. For this reason, balancing the polypropylene fibre admixture and ductility value is a widely used method while increasing the compression strength of concrete in recent years. However, comprehensive experimental studies shall be done to see the effect of different polypropylene fibre admixtures on compression strength of concrete. It becomes more complicated and unpredictable with polypropylene fibre admixture to concrete which is non-homogenous, anisotropic and composite material. Therefore, there is still deficiency in experimental data while there are many completed studies. To this end, ANN analysis is suitable to create software about prediction and complete the deficient experimental data (Siddique *et al.* 2011, Yeh 1998, Guang and Zong 2000, Zurada 1992, Lee 2003).

Solution methods improve with the development of modern computing science. ANN, fuzzy set theory, genetic algorithms, specialized systems take place among these methods. Proven theories of ANN and other logic programming techniques attract many researchers attention. In our day, there are several studies in progress about ANN analysis in civil engineering and especially in concrete technique (Siddique *et al.* 2011, Yeh 1998, Guang and Zong 2000, Zurada 1992, Lee 2003, Atici 2011, Ashrafi *et al.* 2010, Slonski 2010, Onal and Ozturk 2010, Prasad *et al.* 2009).

Selected studies by using ANN analysis method in the literature which are close to this study will be mentioned. In their study, Siddique *et al.* (2011) presents a comparative performance of the models developed to predict 28 days compression strengths using neural network techniques for data taken from literature and data developed experimentally for SCC containing bottom ash as partial replacement of fine aggregates. The data used in the models are arranged in the format of input parameters that cover the contents of cement, sand, coarse aggregate, fly ash as partial replacement of cement, bottom ash as partial replacement of sand, water and water/powder ratio, super plasticizer dosage and output parameters are 7-days and 28-days compression strengths respectively. The importance of different input parameters is also given for predicting the strengths at various ages using neural network. The model developed from literature data could be easily extended to the experimental data, with bottom ash as partial replacement of sand with some modifications.

In his study, Slon'ski (2010) gives a concise overview of three approaches to nonlinear regression modeling with feed forward neural networks, involving the use of evidence framework and full Bayesian inference with Markov chain Monte Carlo stochastic sampling. The article then presents an empirical assessment of these approaches using a benchmark regression problem for compression strength prediction of high performance concrete. Results on applying various methods to benchmark dataset show that Bayesian approach with the MCMC sampling approximation of learning and prediction gives the best prediction accuracy.

In the Onal and Ozturk (2010) study, artificial neural network analysis was performed to establish a relationship between micro structural characteristics and compression strength values of cement mortar. Pore properties such as pore area ratio, total pore length, total dendrite length and average roundness, and paste properties such as hydrated part area and unhydrated part area ratios were approached as micro structural characteristics obtained by digital image analysis. These micro structural quantities were correlated with compression strength values of cement mortar incorporating with the chemical admixtures by different dosages, which resulted as several micro structural characteristics. Artificial neural network (ANN) analysis indicated that by using ANN as non-linear statistical data modeling tool, a strong correlation between the micro structural properties of cement mortar and compression strengths can be established.

In the Prasad *et al.* (2009) study, an artificial neural network (ANN) is presented to predict a

28-days compression strength of a normal and high strength self compacting concrete (SCC) and high performance concrete (HPC) with high volume fly ash. The ANN is trained by the data available in literature on normal volume fly ash because data on SCC with high volume fly ash is not available in sufficient quantity. Further, while predicting the strength of HPC the same data meant for SCC has been used to train in order to reduce computational effort. The compression strengths of SCC and HPC as well as slump flow of SCC estimated by the proposed neural network are validated by experimental results.

Concrete is a highly nonlinear material, so modeling its behavior is a difficult task. However, the artificial neural network (ANN) was proved to be able in predicting the concrete compression strength, without the need of specific equations. Also, its application would reduce the time and cost required for making specimens and the 28 day waiting period before they could be tested. The ANNs have recently been widely used to model some of the human activities in many areas of science and engineering. They need sufficient input-output data, which may be theoretical, experimental or empirical. ANNs can deal with incomplete and noisy data, which is the predominant case in engineering applications.

In consideration of the studies in the literature which are summarized above, compression strength values of polypropylene fibre mixed concrete are obtained in experimental studies and ANN analysis is performed according to advanced software to compare the both experimental and predicted results. After 156 specimens according to 26 different polypropylene fibre admixtures are produced, 7 and 28-day compression strength of concrete values are determined. 126 experimental results are used in training process of ANN analysis and the rest is left for test process to see the stability of both results.

2. Experimental study

2.1 Test specimen and materials

In this study, an experimental study was performed in order to train ANN computer software in the first place. Main variable in the experimental study is the rate of polypropylene fibre. 6 specimens for each fibre ratio are molded and this process is repeated for 26 times. Thus, 156 specimens have been produced. Three of produced specimens are evaluated according to 7-days strength values and the rest three are evaluated according to 28-days strength values.

To remove the differences between specimens under the effect of time, 7-days and 28-days strength tests have been performed on the same day for 26 different polypropylene fibre ratios. In this experimental study, cement, gravel, sand, chemical admixture, polypropylene fibre and water are used to constitute the specimens. Prepared specimens are molded. Finally, strength values of specimens for 7 and 28 days are obtained by cracking the specimens in the testing apparatus.

After, sand, cement and gravel are mixed properly, chemical admixture is added. By this way, the specimen becomes more fluid. Finally, polypropylene fibre is mixed with water and added to the mixture homogeneously. Prepared specimens are molded for six times. Three of them are evaluated according to 7-days strength values and the rest is assessed according to 28-days strength values. This process is repeated for 26 specimens as given in Table 1. In the end, 156 strength values are obtained.

Aggregate of the study is received by two types as sand and gravel and properly mixed according to the standards in the place of production. Some important properties of sand and

Table 1 Material quantities and strength values (MPa) of specimens in experimental study

Spec.	Cement (kg/m ³)	Gravel (kg/m ³)	Sand (kg/m ³)	Chemical admixture (kg/m ³)	Polypropylene Fibre (kg/m ³)	Water (kg/m ³)	Strength values of 7-days	Strength values of 28-days
1	325	817	994	2,6	0	195	26,6	38,5
2	325	817	994	2,6	1	195	24,3	35,8
3	325	817	994	2,6	1,1	192	23,8	33,5
4	325	817	994	2,6	1,2	189	25,6	34,7
5	325	817	994	2,6	1,3	186	23,1	35,8
6	325	817	994	2,6	1,4	183	24,9	34,4
7	325	817	994	2,6	1,5	180	22,8	35,1
8	325	817	994	2,6	1,6	177	22,5	34,3
9	325	817	994	2,6	1,7	174	23,6	32,2
10	325	817	994	2,6	1,8	171	23,1	34,5
11	325	817	994	2,6	1,9	168	22,3	33,7
12	325	817	994	2,6	2	165	21,5	30,7
13	325	817	994	2,6	2,1	162	24,4	30,6
14	325	817	994	2,6	2,2	159	22,2	31,7
15	325	817	994	2,6	2,3	156	21,3	30,9
16	325	817	994	2,6	2,4	153	20,7	32,3
17	325	817	994	2,6	2,5	150	20,4	31,6
18	325	817	994	2,6	2,6	147	21,4	28,6
19	325	817	994	2,6	2,7	144	19,5	27,2
20	325	817	994	2,6	2,8	141	19,8	27,8
21	325	817	994	2,6	2,9	138	20,2	25,6
22	325	817	994	2,6	3	135	18,1	26,8
23	325	817	994	2,6	3,1	132	19,3	23,2
24	325	817	994	2,6	3,2	129	19,5	24,5
25	325	817	994	2,6	3,3	126	17,6	23,9
26	325	817	994	2,6	3,4	123	17,6	23,4

Table 2 Properties of aggregates on concrete production

Aggregate	Particle class (mm)	DYK particle density (mg/m ³)	Water absorption rate (%)
Fine aggregate	Aggregate (0/4)	MB1.1 2,70 ± 0,03	1,00 (Maximum)
Fine aggregate	Aggregate (0/4)	MB2.5 2,67 ± 0,03	1,30 (Maximum)
Coarse aggregate	Aggregate (4/16)	2,70 ± 0,03	0,72 (Maximum)
Coarse aggregate	Aggregate (11/22)	2,70 ± 0,03	0,65 (Maximum)

Table 3 Physical and chemical properties of PÇ 42,5 CEM I 42,5 R Portland cement

Physical properties			
	Unit	Standard	Cement
Initial set	Minute	Min. 60	170
Final set	Minute	-	220
Specific gravity	gr/cm ³	-	3,13
Volume expansion	cm	Max. 10	1
Specific surface	cm ² /gr	-	3640
Liter weight	gr/l	-	975
Strength values of 2-days	MPa	Min. 20	27
Strength values of 28-days	MPa	42,5/-2,5	58
Chemical properties			
SO ₃	%	Max. 4	2,7
MgO	%	-	1,1
Ignition Loss	%	Max. 5	2,4
Insoluble Matter	%	Max. 5	0,6
Cl	%	Max. 0,1	0,01>
Total Alkali Na ₂ O+0.658 K ₂ O	%	-	0,51
Free Lime	%	-	1,0

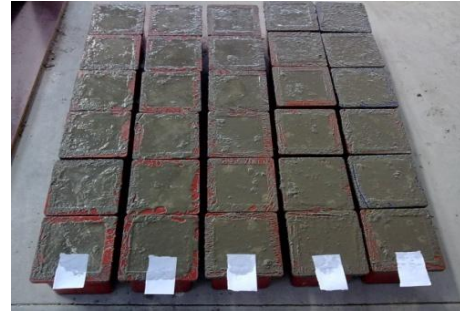
Table 4 Properties of polypropylene fibre

Chemical structure	% 100 polypropylene fibre
Specific gravity	0,91 g/cm ³
Length of the fibre	12 mm
Diameter of the fibre	18 Micron-Nominal
Water absorption	Trace Amount
Melting point	160°C
Ignition temperature	365°C
Heat conductivity	Low
Electrical conductivity	Low
Specific surface area of the fibres	250 m ² /kg
Acid resistance	High
Alkali resistance	% 100
Tensile strength	300 – 400 N/mm ²
Elasticity module	~ 4000 N/mm ²

gravel types of aggregates for concrete production are given in Table 2. Densities of the used aggregates are in accordance with the standards and water absorption values of them are considerably low. In addition, they are extremely appropriate materials. Clinker is made up of materials such as; limestone, marn, clay, iron ore, drossy ash, bauxite etc., by mixing, crushing and burning them in proper ratios. By crushing the clinker with some hardening regulator (usually gypsum) and mixing it with water after a while, Portland cement is obtained. Cement in the concrete mixture is PÇ 42,5 CEM I 42,5 R Portland cement and produced according to TS EN197-1:2002 standards. Portland cement chosen for this study is frequently used in high strength structures, concrete poured in cold weather, precast concrete structures, tunnel formwork systems, construction chemicals and foundation concrete applications. Physical and chemical properties of the used cement are given in Table 3.



(a) 150 × 150 mm cubic concrete molds



(b) Fresh concrete in molds



(c) Concrete specimens after cure process

Fig. 1 Example pictures during production steps of specimens

It is proved in many studies that polypropylene fibres increase the durability properties of concrete. These fibres do not have a negative effect on strength and they usually increase it in many cases. There is such a period of time in plastic phase of the concrete that, internal stresses in the concrete is much bigger than the carrying capacity of it. Cracks can be seen even soon after placing the concrete in the mold. Air temperature during overall drying, cracks according to wind and concrete temperature affect the impermeability of the concrete negatively. All these cracks are generally named as shrinkage cracks. By adding polypropylene fibres into the concrete, ratio of shrinkage cracks decrease and even disappears. Polypropylene fibres also minimizes the size of these cracks. In the scope of the experimental study, 26 different ratios are chosen for polypropylene fibres. Amount of the fibres varies between 0.1% and 0.34% by volume. After mixing high speed for 5 minutes, polypropylene fibres is added into concrete-water mixture and then the mixing process continues for another 5 minutes adding on to concrete mixture. Dosage of polypropylene fibres can be increased in some cases where wearing resistance and intensity micro reinforcement are necessary. Axial tensile strength of the polypropylene fibres is 700 N/mm² in the study. Mixing procedure of the fibres and material strengths are taken from the manufacturer company and some important properties are given in Table 4. Water which is added into the concrete mixture shall be drinkable. Furthermore, salt shall be found in the water. For this reason, water in the municipal water system is appropriate and used in experimental studies. Produced concrete is placed into the 150 × 150 mm sized cube molds. The mixture is placed without any space by using vibrating machine. The specimens take positions in the cure tank after spending 24 hours in the molds. After the specimens are kept in the cure tank for 5 days, they preserved in the laboratory environment for the last day to be test the 7-days strength values of them. For the same

reason, the 28-days strength tests are performed after keeping the specimens in the cure tank for 26 days and 1 day in the laboratory environment. Examples of the pictures from producing stages are shown in Fig. 1.

2.2 Test setup

In the study, experimental analyses of the specimens are performed by using a computer aided press machine. Loading speed is constant in all tests. Computer aided full automatic concrete test press machine which has 2000 kN capacity has high mechanical strength to provide minimum deformation and it is appropriate for usage consistently. Concrete test press machine starts the experiment with closed circuit hydraulic pump. The space between upper moving head and concrete specimen closes swiftly and breaking process begins after taking the pre stress of concrete specimen. The system records the peak point with the breaking of the specimen and it unloads the press by stopping the hydraulic pressure automatically. Loading speed of the press is entered automatically and the system calculates the section areas of the concrete specimens. Thus, it selects the loading speed. Unit of the applied force is $\text{N/mm}^2/\text{sec}$ and can be followed. Examples of the pictures from testing apparatus and from specimens after experiments are shown in Fig. 2.

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Positive effect of polypropylene fibres on concrete behavior can be seen after analyses by investigating the crack forms. When crack forms of reference specimens without polypropylene fibres are investigated, it is clearly observed that lower longitudinal and transverse deformation values occur and specimens divide into big components because of the fracture surface during tests. On the other hand, polypropylene fibre concrete specimens reach breaking point with bigger displacement values and their breaking surfaces preserve their completeness even there are some cracks occurred after tests.

The variables that are investigated in this study are polypropylene fibre and water quantities. The effect of combination of these two parameters on compression strength after 7 and 28 days curing time is given at Fig. 3. While polypropylene fibre ratio is increased, water mixture ratio is decreased. While decreasing the water mixture ratio, increase in concrete compression concrete is expected, but increase in polypropylene fibre ratio is affected more dominantly and compression strength of concrete is dropped with increasing polypropylene fibre ratio. Decrease in compression strength is encountered at both 7-days and 28-days curing time. The decrease in compression strength ratio is low at the beginning and then increased with increase in polypropylene fibre ratio.

Strength values of 7-days and 28-days after experimental analyses are given in Table 1. There have not been significant changes on strength values according to fibre contribution. However,



(a) Concrete test press machine (YKM-C205) with 2000 kN capacity



(b) View of the cubic mold during axial pressure test

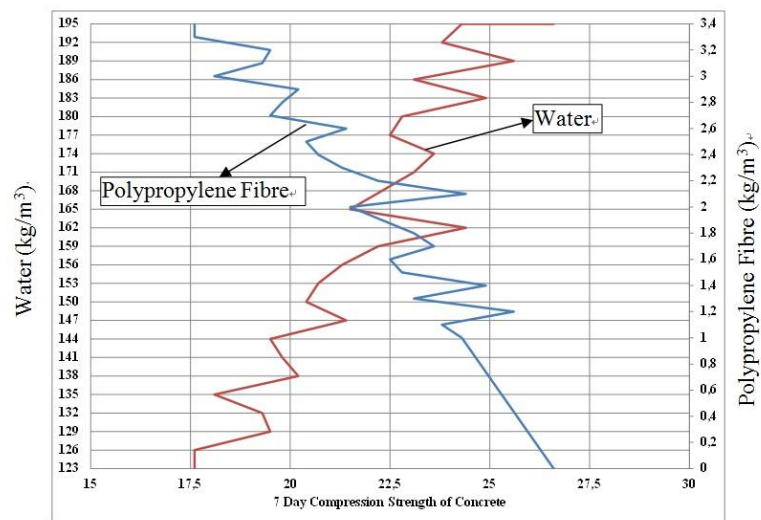


(c) Reference specimens after pressure test



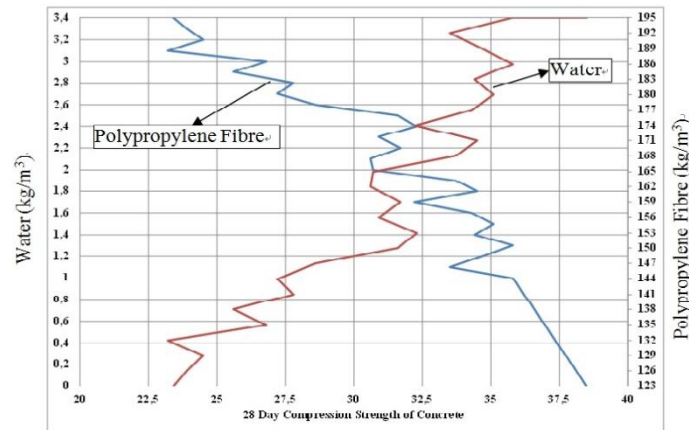
(d) Polypropylene fibre concrete specimens after Pressure

Fig. 2 Test setup and specimens after experimental analyses



(a) 7 Day compression strength of concrete

Fig. 3 Compression strength variation graphs with respect to water and fibre ratio



(b) 28 Day compression Strength of Concrete

Fig. 3 Continued

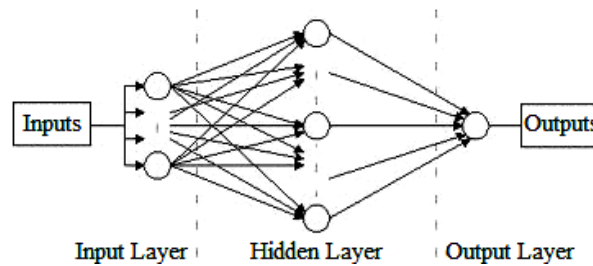


Fig. 4 Architecture of ANN model

compression strengths are affected when fibre ratio increases in the mixture. There aren't big changes observed on the strength until this ratio reaches %0.2 value. On the other hand, Strength values of 7-days and 28-days start to decrease after exceeding %0.2 fibre ratios. Important decreasing on strength is seen when fibre ratio reaches %0.26. When the highest fibre ratio is handled by %0.34 ratio, strength value of 7-days decreases by %51 and strength value of 28-days decreases by %65 according to reference specimens. Finally, it is seen after experimental analyses that, fibre ratio between %0.1 and %0.20 can be used in applications without significant decrease on strength.

3. Artificial neural networks

An artificial neural network is a system based on the operation of biological neural networks, in other words, is an emulation of biological neural system. Artificial neural network (ANN), usually called neural network (NN), which is a mathematical model or computational model that is inspired by the structure and/or functional aspects of biological neural networks. ANN is known as a complex system of the neurons that are connected each other with different influence levels. It is composed of a large number of highly interconnected neurons working in unison to solve specific

problems. Computation is modeled as a large network of interconnected simple processors and ANN can be trained to recognize input patterns and produce appropriate output responses. The problems that have sufficient training data are suitable for ANN. Prediction of the complex problems and fast evaluation of new examples are the main advantages of ANN.

ANN are used in many scientific study fields such as, classification, modelling and prediction. In general terms, ANN is a complex system that can be evaluated as connecting of neurons or simple processors with different influence levels. Studies which have been started by modelling the neurons in human brain mathematically, are now available in basic sciences during the last decade. This is because, ANN is an alternative way for problems which are difficult to solve with classic methods.

The prevalent type of artificial neural network consists of three or more layers, including an input layer, an output layer and a number of hidden layers in which neurons are connected to each other with modifiable weighted interconnections as seen in Fig. 4. The input layer consists of number of nodes receiving data from independent variables. Therefore, number of nodes in input layer is equal to the number of input variables of the problem. The hidden layer receives information from input layer by using the applied weights and pre-specified activation functions. The output layer receives information from the hidden layer and sends results to an external recreant. The number of nodes in the output layer is equal to the number of output variables. The ANN architecture is commonly referred to as a fully interconnected feed forward multilayer perceptron. In addition, there is a bias, which is only connected to neurons in the hidden and output layers with modifiable weighted connections. The number of neurons in each layer may vary depending on the problem.

Suitable architecture is required for design of ANN. Back Propagation is the most common neural network learning algorithm of ANN. This is due to its relatively simplicity and together with its universal approximation capacity. The Back Propagation algorithm defines a systematic way to update the synaptic weights of multi-layer feed forward supervised networks composed of input, hidden and output layers. The back propagation supervises learning process which is based on the gradient descent method that usually minimizes the sum of squared errors between the target value and output of the neural network. This algorithm looks for the minimum of the error function in weight space using the method of gradient decent

4. Numerical analysis

In this study, a multilayer feed forward back propagation neural network is applied by using the neural network toolbox of the Matlab software. Several Matlab subroutines have been developed and various other commands have been used to perform the task successfully. The study is concerned with the prediction of the strength values using ANN. The database includes 20 data which is composed of 120 experimental studies for training and 6 data that is formed of 36 experimental studies are taken into consideration to test the network. While cement, gravel, sand and chemical admixture are taken as constant inputs, polypropylene fibre and water quantities are taken as varied ones. On the other hand, strength values of 7 and 28 days are output parameters of the network. A single hidden layer also takes place in the architecture of network.

The most convenient architecture of network was determined after trials. The topology of the network has been organized to consist of network consists of input, hidden and output layers. Inputs and outputs are normalized in the (-1:1) range by using simple normalization methods.

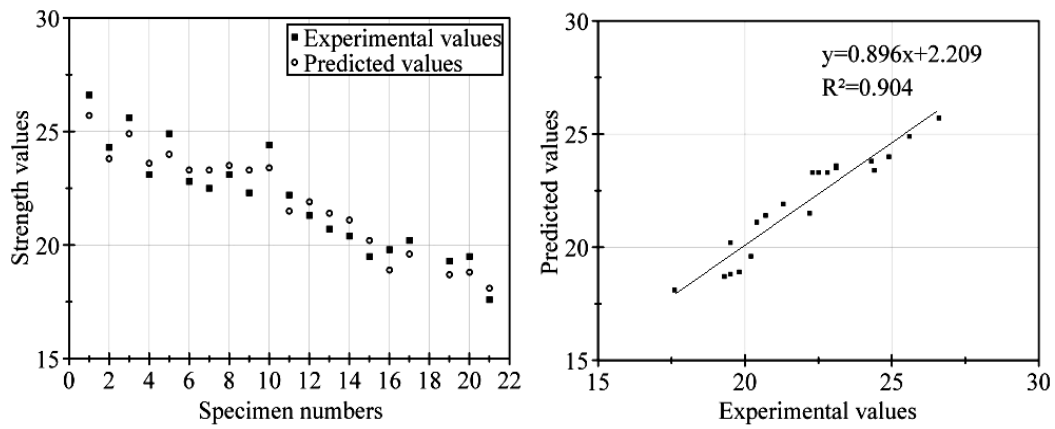


Fig. 5 Dispersion and performance of training set (7-days strength values (MPa))

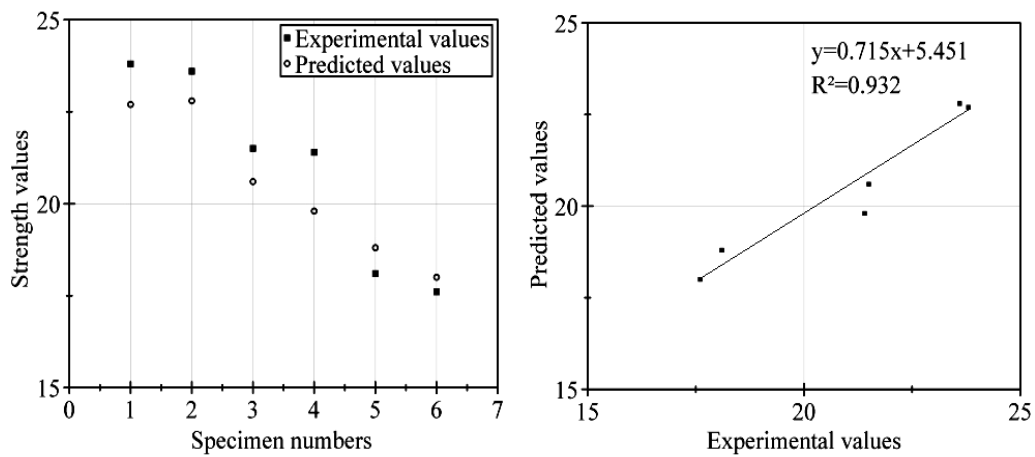


Fig. 6 Dispersion and performance of testing set (7-days strength values (MPa))

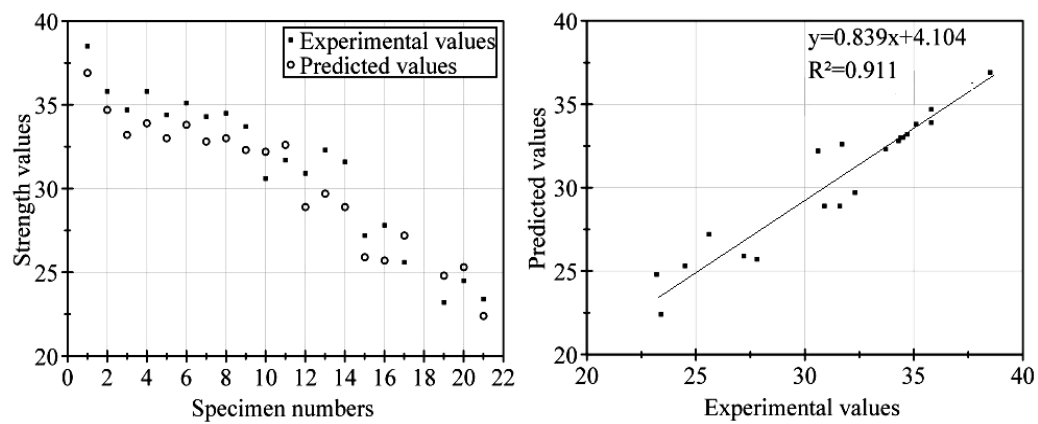


Fig. 7 Dispersion and performance of training set (28-days strength values (MPa))

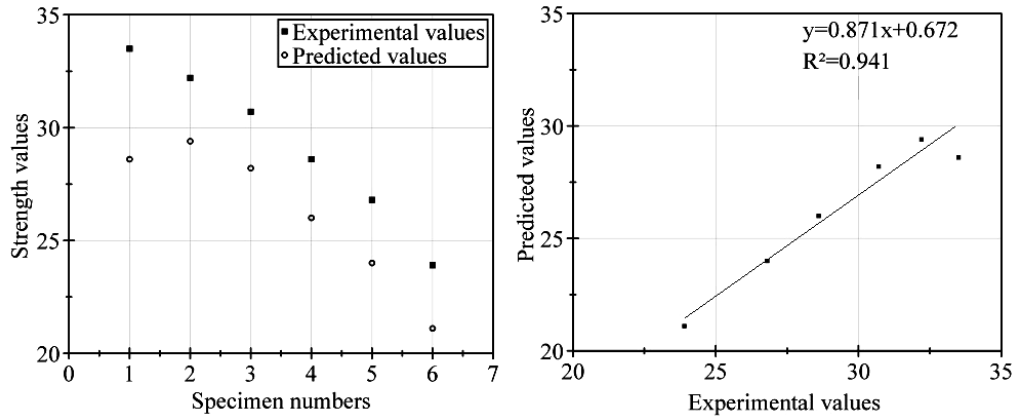


Fig. 8 Dispersion and performance of testing set (28-days strength values (MPa))

Table 5 Correlation coefficients

Strength values of 7-days		Strength values of 28-days	
R^2 (training)	R^2 (test)	R^2 (training)	R^2 (test)
0.904	0.932	0.911	0.941

Scaled Conjugate Gradient (SCG) is used as the training function. 4000 iterations are performed to find out the optimum result.

The performance of the network has been evaluated by calculating the coefficient of determination for the experimental and predicted values of the data set. The performance of training and testing sets of the ANN are given in Figs. 5-8. It is seen that the set data have been also simulated by using the established network and outputs that are marked in the same figure. As it's seen in both of the figures, calculated and predicted values are close each other.

Strength values are evaluated according to ANN analysis and correlation coefficients (R^2), are obtained according to training and test process representing a strong relationship between for the investigated parameters as given in the Table 5. This table gives information about the measured and predicted strength values by ANN analysis with (R^2) coefficients.

5. Conclusions

Fibre compounded concrete members are used in plates, airports, ports, stairways, prefabricated concrete members, concrete and reinforced concrete pipes. Ductility of fibre compounded concrete specimens depends on fibre quantity. While void ratio and water absorption rate increase, weight per unit of volume and compression strength decrease according to fibre increment.

There have been many studies over concrete technology by researchers. Since experimental studies require work force, they reduce working performance. Therefore, artificial neural networks analysis which predicts experimental data successfully is an alternative way to overcome difficulties of experimental studies. ANN analysis performs complicated and non-linear calculations swiftly and easily. Multi-layered neural network is used commonly and consists of

minimum three layers. There may be more than one hidden layers between input and output ones.

A computer program was written to obtain the coefficients for the proposed models. Strength values of 7 and 28 days are determined by experimental analyses in the first place. Henceforth, these values are tried to be predicted according to ANN. The input and output data were normalized between the range of -1 to 1, in the ANN analysis. Since experiment results and ANN model exhibit good correlation, the proposed ANN model is a notable alternative approach for prediction and programming by using ANN analysis. Eventually, strong relationship is established between calculated and predicted values. The correlation coefficient values are determined $R^2 = 0.9089$ and $R^2 = 0.9439$ for 7-days strength values and $R^2 = 0.9011$ and $R^2 = 0.9334$ for 28-days strength values according to training and test process respectively. The results show that a significant model has been established between the parameters by measured and predicted values.

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