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Prediction of Hybrid fibre-added concrete strength using artificial neural networks

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Abstract. Fibre-added concretes are frequently used in large site applications such as slab and airports as well as in bearing system elements or prefabricated elements. It is very difficult to determine the mechanical properties of the fibre-added concretes by experimental methods in situ. The purpose of this study is to develop an artificial neural network (ANN) model in order to predict the compressive and bending strengths of hybrid fibre-added and non-added concretes. The strengths have been predicted by means of the data that has been obtained from destructive (DT) and non-destructive tests (NDT) on the samples. NDTs are ultrasonic pulse velocity (UPV) and Rebound Hammer Tests (RH). 105 pieces of cylinder samples with a dimension of 150 × 300 mm, 105 pieces of bending samples with a dimension of 100x100x400 mm have been manufactured. The first set has been manufactured without fibre addition, the second set with the addition of %0.5 polypropylene and %0.5 steel fibre in terms of volume, and the third set with the addition of %0.5 polypropylene, %1 steel fibre. The water/cement (w/c) ratio of samples parametrically varies between 0.3-0.9. The experimentally measured compressive and bending strengths have been compared with predicted results by use of ANN method.

Keywords: fibre-added concrete; hybrid fibre; compressive; bending, non-destructive test; artificial neural network

1. Introduction

Fibres are frequently used in structural and non-structural concretes as it improves many mechanical properties of concrete such as compressive strength, bending strength, ductility and toughness. It is a difficult and effort-requiring process to determine the behaviours of fibre-added concretes by use of destructive experimental methods such as core - taking method. For that reason, in order to determine the mechanical properties of the concretes, it is more advantageous to use NDT methods. NDT methods which give no harm to the structure and structural elements are frequently used in recent years in order to assess the quality of the concrete. RH and UPV methods are most commonly used NDT methods (Komlos *et al*. 1996; Demirboğa *et al*. 2004; Hoła and Schabowicz 2005; Kewalramani and Gupta 2006; Yaman *et al*. 2006; Ulucan *et al*. 2008; Liu *et al*. 2009; Trtnik *et al*. 2009; Bilgehan and Turgut 2010; Bilgehan and Turgut 2010; Shariati *et al*. 2011; Mazloom and Yoosefi 2013; Sheena *et al*. 2013, Ercikdi *et al*. 2014).

ANN was commonly used to predict strength of concrete having different properties with various tests. Contrary to the traditional prediction methods, ANN can be easily adapted new data

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and continuously re-trained. ANN were frequently carried out together with NDT and easily reached mechanical properties of concrete.

Hoła and Schabowicz (2005) researched the compressive strength of concrete by using NDT methods. A data set based on results of representing a wide range of strength concretes by different NDT methods such as UPV, RH and the pull-out test was used to train and test for an ANN. Finally, it is proposed to determine the compressive strength of concrete by using several NDT methods. Altun *et al*. (2008) studied the usability of ANN to predict the compressive strength of steel fibre added lightweight concrete. For this purpose, normal strength lightweight concrete with 350, 400, and 450 kg/m^3 cement dosages were produced. The steel fibres were added to each specimen at the various dosages. The test results obtained from the ANN were compared with the multi linear regression technique based on mean square error, mean absolute error, and correlation coefficient criteria. ANN predicted the compressive strength of steel fibre added lightweight concrete better than did the multi linear regression technique. Trtnik *et al*. (2009) aimed to easily and reliably predict the compressive strength of concrete by using only the UPV value and some mix parameters of concrete. The relationship between UPV, static and dynamic Young's modulus and shear modulus was also analysed. Based on the experimental results, a numerical model was established with ANN. ANN was successfully used in modelling the velocity–strength relationship. Bilgehan and Turgut (2010a) determined relationship between concrete compressive strength, UPV and density values by using the experimental data obtained from many cores taken from different reinforced concrete structures by using ANN. It was shown that ANN approach could be used effectively to predict the compressive strength of concrete by using UPV and density data. Shariati *et al*. (2011) established a correlation between the compressive strengths obtained from compressive tests, UPV and RH tests. These tests had been used to determine the concrete quality by applying regression analysis models between compressive strength of in-situ concrete on existing building and test values. The test results showed that the RN method was more efficient in predicting the strength of concrete. Besides, a combined method for the above two NDT tests were used. The more reliable results that were closer to the true values were obtained with combined methods. Ercikdi *et al*. (2014) presented the strength and UPV properties of cemented paste backfill produced from two different mill tailings. It was concluded that the UPV test could be suitably used for the rapid estimation of the strength and quality of cemented paste backfill samples even using small samples.

In this study, an ANN model has been developed in order to predict the compressive and bending strengths of the fibre-added and non-added concretes by use of DT and NDT methods. w/c ratio, steel and polypropylene fibre ratio which have effects on the mechanical properties of the concrete have been considered as variables and a wide range of data network has been investigated. The UPV and RN values of the samples have been determined by use of NDT methods. Then compressive and bending strengths of these samples have been obtained by use of DT tests. Finally, by means of the ANN model that was developed, compressive and bending strengths of fibre-added and non-added concretes have been predicted by use of NDT methods. A good degree of coherency was observed between predicted and measured values. The model that was developed makes it possible to easily predict the compressive and bending strengths of the fibre-added and non-added concretes by use of non-destructive tests instead of making destructive tests on the structure.

2. Experimental program

2.1 Materials and mix proportions

In this study, 105 pieces of cylinders, 105 pieces of bending samples with different w/c ratios have been manufactured in the Celal Bayar University laboratories by the author. w/c ratios have been changed as 0.3, 0.4, 0.5, 0.6, 0.7, 0.8 and 0.9. In addition, concrete was added with steel and polypropylene fibres at the production stage. Steel fibre was added to the concrete by %0.5 and %1, and polypropylene fibre by %0.5 in terms of volume. For each set of the concrete, 5 pieces of cylinders, 5 pieces of bending samples have been manufactured. The geometry of steel fibres was hooked end type. The fibre length (l) in concrete was 60 mm, the diameter (d) was 0.75 mm, aspect ratio (l/d) was 80. Polypropylene fibres are homopolymer type and yarn length is 18 mm. For the production of concrete, 0-4 mm natural sand for fine material and 4-8 mm and 8-16 mm crushed stone has been used. Polycarboxylic based superplasticizer admixture was used for obtaining good workability in fresh mix. Portland cement has been used for concrete production. Dry materials have been mixed for 3 minutes, and then polypropylene and steel fibres have been added in the mixture, respectively. Finally water has been added. The materials and ratios used for concrete production have been shown in Table 1. Non-fibre concrete mixtures have been named as REF and fibre concrete mixtures as HF (Hybrid Fibre). The numbers following “HF” represent w/c and steel fibre ratios, respectively. All samples have been cured under + 20 ^{o}C until the end of 28 days.

Table 1 Materials and ratios used for concrete production

No	Mix Code	Sand (kg/m^3)	4-8 (kg/m^3)	8-16 (kg/m^3)	Water (kg/m^3)	Cement (kg/m^3)	W/C	Steel Fibre % in volume	Polypropylene Fibre % in volume
1	REF0.9/0	1025	410	610	170	188	0.9	0	0
2	HF0.9/0.5	1025	410	610	170	188	0.9	0.5	0.5
3	HF0.9/1.0	1025	410	610	170	188	0.9	1.0	0.5
4	REF0.8/0	1005	405	605	170	212	0.8	0	0
5	HF0.8/0.5	1005	405	605	170	212	0.8	0.5	0.5
6	HF0.8/1.0	1005	405	605	170	212	0.8	1.0	0.5
7	REF0.7/0	995	400	595	170	242	0.7	0	0
8	HF0.7/0.5	995	400	595	170	242	0.7	0.5	0.5
9	HF0.7/1.0	995	400	595	170	242	0.7	1.0	0.5
10	REF0.6/0	975	390	585	170	282	0.6	0	0
11	HF0.6/0.5	975	390	585	170	282	0.6	0.5	0.5
12	HF0.6/1.0	975	390	585	170	282	0.6	1.0	0.5
13	REF0.5/0	945	380	565	170	340	0.5	0	0
14	HF0.5/0.5	945	380	565	170	340	0.5	0.5	0.5
15	HF0.5/1.0	945	380	565	170	340	0.5	1.0	0.5
16	REF0.4/0	905	360	545	170	420	0.4	0	0
17	HF0.4/0.5	905	360	545	170	420	0.4	0.5	0.5
18	HF0.4/1.0	905	360	545	170	420	0.4	1.0	0.5
19	REF0.3/0	835	335	500	170	560	0.3	0	0
20	HF0.3/0.5	835	335	500	170	560	0.3	0.5	0.5
21	HF0.3/1.0	835	335	500	170	560	0.3	1.0	0.5

2.2 Experimental method

In this study, 2 DT and 2 NDT tests, in total 4 different tests have been performed: uniaxial compressive test, 4 point bending test, RH and UPV tests. Some of the samples that have been subjected to test have been shown in Fig. 1(a). On the samples, first of all RH and UPV tests-which are non-destructive-have been applied and then cylinder and bending samples have been subjected to destructive uniaxial compressive and four point bending tests, respectively as illustrated in Fig. 1.b and 1.c. Non-destructive UPV and RH tests have been shown in Fig. 1.d and 1.e, respectively (Hoła and Schabowicz 2005).

The velocity of ultrasonic pulses travelling in a solid material is related to the density and elastic properties of the material. Although UPV method has some difficulties; it is one of the most popular non-destructive tests of today. The UPV equipment contains a transmitter, a receiver and an electronic clock. The velocities of P waves were calculated from the measured travel time and the distance between the transmitter and receiver. In this study, UPV tests have been made in accordance with ASTM C 597-97 standard. Measurements has been performed on two faces of elements by direct (measure in direct) method.

The RH test is a convenient NDT. The surface of hardened concrete is struck with the hammer, and concrete compressive strength is predicted via the surface rebound value. When the RH test is performed, kinetic energy from the impact and amount of lost kinetic energy affect the RN. Rebound energy is correlated with the concrete strength and rigidity (Liu *et al*. 2009). Rebound tests of the concrete specimens were performed using a digital hammer apparatus according to ASTM C 805. At least 20 measurements were taken at different points upon each sample.

The compressive strength properties of the concrete mixtures were determined according to standards proposed by ASTM C 39. In order to carry out the uniaxial compressive tests of concretes with or without fibre, 2500 kN capacity- hydraulic press machine has been used. A total of 105 pieces of 150×300 mm cylinder samples were produced and subjected to uniaxial compressive test. The compressive strengths that were obtained as a result of tests have been given in Table 2. Four point bending test has been performed by use of 100 kN capacity-bending test device. 105 pieces of bending samples (dimensions:100×100×400 mm) have been manufactured. The bending strengths obtained as a result of tests have been given in Table 2.

In the samples with a low w/c ratio which have less porosity as a result of tests, UPV is high, whereas the addition of fibres in the concrete decreases the UPV. Despite RN has been impacted from the addition of fibres into the concrete even to a little scale, it has been rather impacted from w/c ratio and it has increased when this ratio decreased.

The decrease of w/c ratio, as expected, increases the compressive and bending strengths of the concrete. Addition of steel and polypropylene fibres into the concrete has increased both the compressive and bending strength of the concrete. In the samples whose steel fibre ratio is %1 and w/c ratio is between 0.7 and 0.9, compressive strengths of the samples has increased by an average of %21 comparing to reference samples, and in the samples whose fibre ratio is %0.5 by an average of %10. Compressive strengths has increased by an average of %8 and %14 in the samples whose w/c ratio is between 0.3 and 0.6, steel fibre ratio is %1 and %0.5, respectively. It has been seen that the fibres are more effective on the compressive strengths of low strength concretes.

Bending strengths increase as the steel fibre ratio increases. The bending strengths of the samples which have %1 steel fibre have increased by an average of %53 comparing to reference samples, and the bending strengths of the samples which have %0.5 steel fibre by an average of

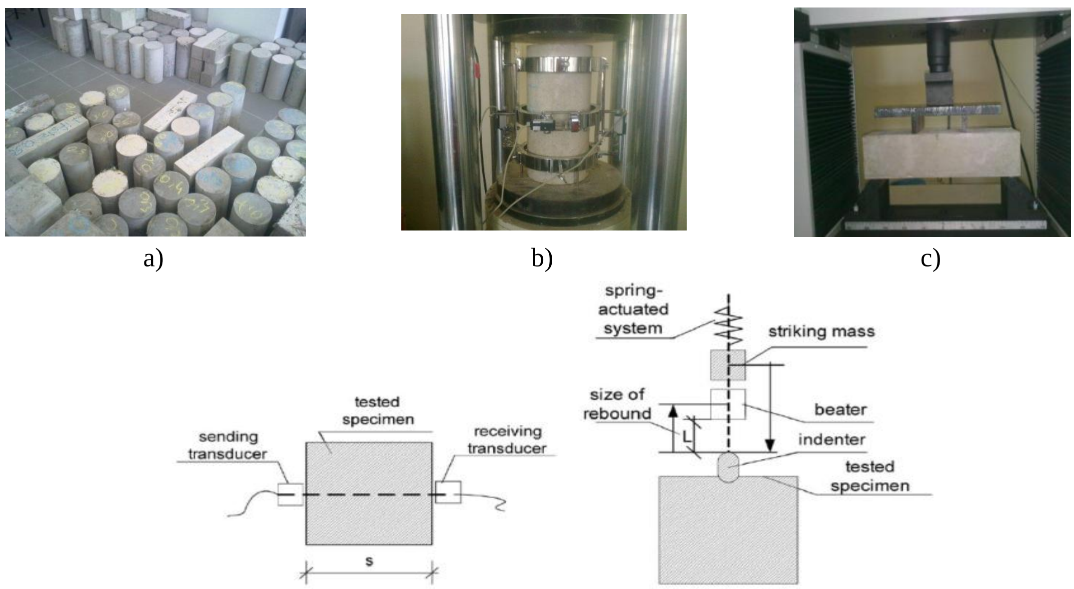
%16. With the impact of the steel fibre, bending samples have been failed in a ductile manner. The fibre impact is more obvious on the bending strengths of the samples with a low w/c ratio. Fibres influence the bending strength rather than compressive strength of concrete.

Table 2 Results of DT and NDT tests

No	Mix Code	Compressive Strength (MPa)	Bending Strength (MPa)	RN	UPV (m/sn)	No	Mix Code	Compressive Strength (MPa)	Bending Strength (MPa)	RN	UPV (m/sn)
1	REF0.9/0	16.6	2.61	27	3865	12	HF0.6/1.0	34.1	7.05	38	3720
		15.2	2.67	25	3840			34.3	7.50	38	3730
		17.4	2.55	27	3875			35.2	7.38	39	3790
		16.1	2.49	27	3850			35.3	6.90	39	3798
		15.7	2.64	26	3820			34.2	6.75	39	3760
2	HF0.9/0.5	18.8	3.30	28	3027	13	REF0.5/0	39.4	5.49	41	4260
		20.0	3.45	29	3102			40.1	5.94	41	4280
		17.9	3.54	28	3010			38.5	5.70	40	4255
		18.3	3.15	28	3040			37.7	5.25	41	4250
		19.1	3.24	29	3050			38.1	5.10	39	4260
3	HF0.9/1.0	23.4	4.44	31	3220	14	HF0.5/0.5	43.8	6.33	43	4071
		22.8	4.65	31	3200			45.5	6.78	45	4126
		23.9	4.26	32	3250			43.5	6.00	44	4070
		22.1	4.35	31	3180			45.7	5.79	45	4150
		22.9	4.50	32	3190			44.9	6.90	44	4100
4	REF0.8/0	24.1	3.15	29	3967	15	HF0.5/1.0	42.8	7.95	43	4005
		22.1	3.33	28	3925			41.0	8.34	42	3870
		22.9	3.03	28	3935			41.7	8.40	42	3950
		24.1	3.27	30	3980			42.9	7.59	43	4020
		23.2	3.23	29	3970			40.6	7.44	43	3800
5	HF0.8/0.5	25.9	3.66	31	3367	16	REF0.4/0	45.2	6.45	43	4410
		26.7	3.90	32	3370			44.1	6.87	45	4390
		24.9	3.48	31	3280			43.8	6.15	43	4370
		26.2	3.81	31	3390			44.6	6.09	43	4380
		25.3	3.36	32	3410			42.9	6.60	43	4320
6	HF0.8/1.0	26.8	5.37	35	3507	17	HF0.4/0.5	50.0	7.59	47	4310
		27.8	5.64	35	3550			48.8	7.20	47	4290
		26.2	4.95	33	3490			50.7	7.98	48	4360
		28.1	5.10	35	3570			50.2	7.80	49	4350
		26.9	5.70	33	3502			49.1	7.50	49	4305
7	REF0.7/0	28.5	4.05	33	4021	18	HF0.4/1.0	47.1	9.24	45	4260
		29.1	4.35	34	4090			48.7	9.66	48	4310
		29.5	4.47	34	4120			46.8	9.60	45	4250
		27.5	3.75	33	4020			47.6	8.94	46	4300
		27.9	3.87	33	4010			48.1	8.85	46	4320

Table 2 Continued

No	Mix Code	Compressive Strength (MPa)	Bending Strength (MPa)	RN	UPV (m/sn)	No	Mix Code	Compressive Strength (MPa)	Bending Strength (MPa)	RN	UPV (m/sn)
8	HF0.7/0.5	29.4	4.56	33	3553	19	REF0.3/0	51.5	7.14	45	4658
		29.7	4.26	33	3520			50.1	7.50	45	4620
		28.9	4.17	32	3490			52.6	7.59	46	4670
		30.6	4.92	33	3610			49.8	6.90	45	4605
		30.9	4.95	33	3602			50.8	6.72	46	4625
9	HF0.7/1.0	32.1	6.24	37	3650	20	HF0.3/0.5	57.1	8.40	50	4440
		31.1	6.48	36	3640			58.8	8.82	52	4490
		32.9	6.60	36	3690			59.1	8.16	52	4520
		31.0	5.94	37	3600			57.9	8.10	52	4455
		33.0	5.85	37	3710			58.6	8.64	50	4470
10	REF0.6/0	32.7	4.68	35	4153	21	HF0.3/1.0	55.5	10.23	50	4444
		32.9	4.50	35	4180			54.7	10.62	49	4418
		31.2	4.35	35	4110			53.9	10.50	49	4400
		33.3	4.89	36	4235			56.1	9.96	50	4470
		33.1	5.04	36	4230			55.9	9.84	49	4430
11	HF0.6/0.5	37.2	5.13	39	3877						
		35.6	5.40	39	3752						
		36.2	5.58	38	3780						
		36.9	4.74	38	3790						
		38.1	4.89	40	3895						



d) e)

Fig. 1 a) Test samples, b)uniaxial compressive, c) bending tests, d) UPV test, e) RH test

3. Artificial neural networks

3.1 Application of ANNs for training and testing

ANNs are the artificial intelligence technique developed with the inspiration from neural system's properties such as ability to derive, define and predict information. ANNs, as in biological neural systems, consist of cells coming together. An ANN structure consists of 3 main layers: input, hidden and output.

Input and output layers contain the date about the incident or problem. The number of neurons in the hidden layer and number of hidden layers are decided by trial and error during the training of the network. Simplified model of artificial neuron have been given in Fig. 2.

x^m represents inputs, w^m represents weight coefficients, net_j represents the net information function which determines the transmittal of information in a network from one layer to another layer, and y_i represents outputs. The net functions which are obtained as the total, minimum, maximum or factors of the weighted inputs refer to the impacts of the whole of these inputs on this cell. In the overall of the modelling studies made, total net function which is found as the total of the weighted inputs is being used. Total net function has been presented in (1):

$$net\ j = \sum_{i=1}^{n} x_i w_{ij} \tag{1}$$

The activation function which converts net input values into net output values can be a linear or non-linear function. In this study, sigmoid function has been used which is frequently used in engineering problems (Kewalramani and Gupta 2006, Altun *et al*. 2008) and which produce net outputs between 0 and 1. Sigmoid function is monotonically increasing, continuous and nonlinear. Sigmoid function has been given in (2):

$$f_{(net\ j)} = \frac{1}{1+e^{-net\ j}} \tag{2}$$

In this study, feed-forward back-propagation training algorithm has been applied which is frequently seen in literature (Bilgehan and Turgut 2010a, Tanarslan *et al*. 2012). This algorithm consists of two phases: feed forward and back propagation. In feed forward, input values are standardized by activation function and net values are obtained as per the net function used and net value is converted into the network's output value by activation function. When the data obtained from the network are compared with the data available, if the errors are big, network shifts to back propagation phase. In this study, generalised delta rule has been used in back propagation phase. Delta learning rule is based on changing the weight coefficients in order to minimise the errors. With the new weight coefficient values, network re-calculates the output values. When the error reaches the desired limit, training of the network is completed. The trained network is tested with the input and output values which have not been previously used. Due to property of the logarithmic sigmoid activation function, all input and output values have been normalized between 0.1–0.9 by use of (3) as

$$z_i = 0.1 + \frac{0.8 \times (x_i - x_{min})}{(x_{max} - x_{min})} \tag{3}$$

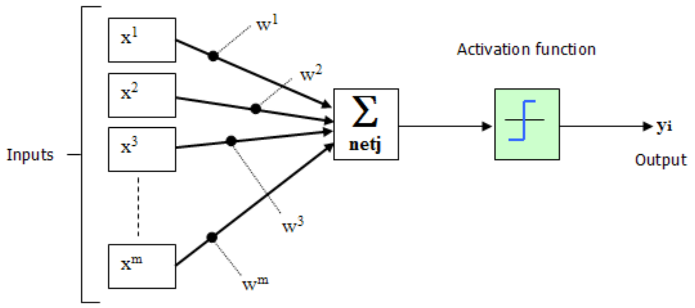


Fig. 2 Simplified model of artificial neuron

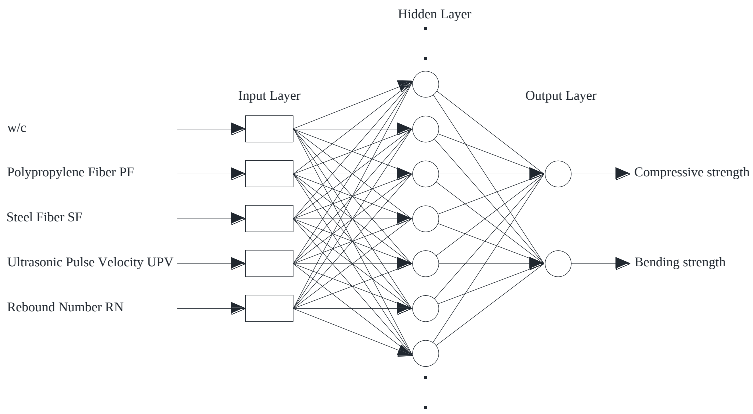


Fig. 3 Structure of the network

The unidirectional, multilayer feed-forward back-propagation and the Levenberg-Marquardt network were selected based on researches in the literature (Hoła and Schabowicz 2005, Altun *et al*. 2008). The Levenberg–Marquardt training algorithm was used for adjusting the weights. The adaptive learning rates were used for the goal of faster training speed and solving local minima problem. The network structure, five inputs, one hidden layer having 10 neurons and 30 epochs for training were used. The input data consisted of w/c ratio, ratio of polypropylene fibre, ratio of steel fibre, RN and UPV. The output data consisted of compressive and bending strengths. The data were randomly divided into data for training (70% of the total data) and testing (30% of the total data) the neural network. In ANN application, the neurons number in hidden layer was parametrically changed ranging from 1 to 10, optimum neuron number was determined and all of determination coefficients (R^2) obtained from training are shown in Table 3. The network structure is shown in Fig. 3.

3.2 Results and Discussions

The performance of the network has been assessed with the determination coefficients (R^2) calculated between the experimental and predicted data sets. The performance of training and test data has been given in Fig. 4-5. A good learning process depends on the number of hidden layer and the number of neurons in the hidden layer. The function of the neurons in the hidden layer reveals the relationship between the input and outputs of network. R^2 values pertaining to the compressive and bending strengths that have been obtained as per parametrically changed neuron numbers have been given in Table 3. In ANN application, maximum R^2 values have been reached when there are 10 neurons in the hidden layer, by making 30 epochs and with μ value 0.02. μ is the learning parameter of Levenberg-Marquardt training algorithm. In this structure, R^2=0.995 in compressive, R^2=0.982 in bending.

In the training period of the network, scatter diagrams between the measured and predicted data sets have been illustrated in Fig. 4. The relationship between compressive data has been illustrated

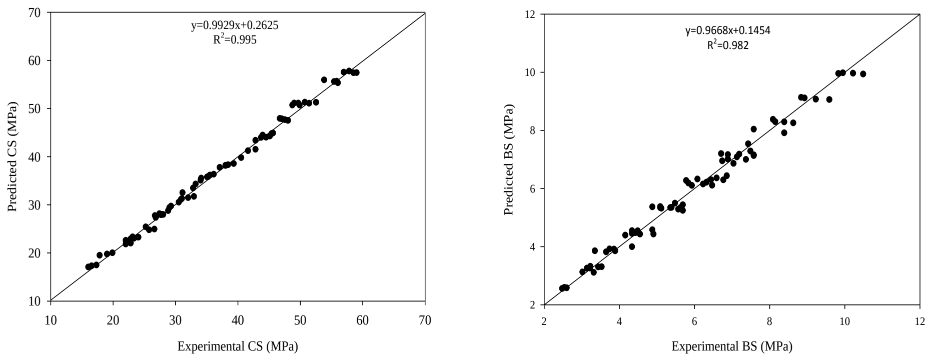


Fig. 4 Performance of training data set

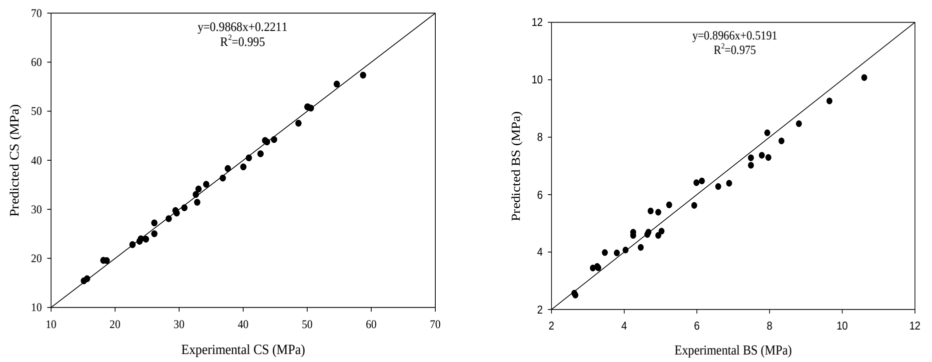


Fig. 5 Performance of test data set

Table 3 Determination coefficients (R^2) obtained from training

Neurons in hidden layer	1	2	3	4	5	6	7	8	9	10
R^2 in Compressive	0.944	0.944	0.953	0.990	0.989	0.994	0.988	0.988	0.992	0.995
R^2 in Bending	0.922	0.921	0.925	0.976	0.982	0.981	0.975	0.974	0.979	0.982

in Fig. 4(a), the relationship between bending data has been illustrated in Fig. 4(b). when Fig. 4 is examined, it is seen that scattering between measured and predicted compressive strengths is little. In other words, these values are on a 45^o line. Similar results were obtained for bending strengths. It has been seen that there is a good degree of coherency between the measured and predicted data sets. At the training phase, measured and predicted compressive and bending strength determination coefficients have been found 0.995 and 0.982 respectively. Also, a good degree of coherency was obtained between the data sets allocated for test (Fig. 5). Fig. 5(a) indicates the relationship between the measured and predicted compressive strengths and Fig. 5(b) indicates the relationship between the measured and predicted bending strengths. It is seen that the scattering of the test data of measured and predicted compressive and bending strengths towards each other is little both in low and high values. The R^2 between the measured and predicted compressive strengths of test data was obtained as 0.995, and the R^2 between the bending strengths as 0.975. These test values proves that developed ANN model is pretty successful.

4. Conclusions

In this study, the compressive and bending strengths of the hybrid fibre-added and non-added concrete samples with w/c ratios varying in the range of 0.3-0.9 has been predicted by ANN application using destructive and non-destructive experimental data. Polypropylene and steel fibres that are used for improving the mechanical properties of the concrete has been added to cylinder and bending samples in certain rates. 105 pieces of compressive and 105 pieces of bending samples have been manufactured. After determining the UPVs and RNs of these samples by NDT methods, these samples have been subjected to compressive and bending tests by DT methods. As a result of tests, decreasing the w/c ratio has increased the compressive and bending strengths of the concrete. Without fibre addition, UPV and RN values of low-porous samples have been observed to increase. Addition of fibres into the concrete has improved the compressive and bending strengths. Fibres are more effective on bending strengths. Fibres have decreased UPV. RN has been impacted from the addition of fibres into the concrete even if such impact is minor, it has been more impacted from w/c ratio and it has increased as this ratio decreased.

By means of the ANN model that was developed, compressive and bending strengths of fibre-added and non-added concretes have been predicted based on w/c, polypropylene fibre amount, steel fibre amount, UPV and RN values. By use of the model developed, it will be possible to easily predict the compressive and bending strengths by use of NDT, UPV and RH test, instead of taking cores from the concrete which is difficult. Data set have been divided into two phases: training and test data. A good degree of coherency was obtained between the measured and predicted data. This coherency also reflects on the determination coefficient which is a performance indicator between data. At the training phase, the R^2 between measured and predicted compressive and bending strengths have been calculated as 0.995 and 0.982 respectively. By use of the developed ANN model, the R^2 values of the compressive and bending strengths pertaining to the data that was allocated for test have been obtained as 0.995 and 0.975 respectively. The fact that yielding R^2 values are very close to 1 indicates that the developed model passes a good training.

Consequently, by use of the developed ANN model, it is pretty simple to predict the compressive and bending strengths of fibre-added and non-added concretes as no core has to be taken hereby. By use of this study, compressive and bending strengths to be determined by use of NDT methods can easily be predicted. Also, this model can be continuously trained with new data and its practicability range can easily be extended.

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