Computers and Concrete, *Vol. 18, No. 1 (2016) 001-016*
DOI: http://dx.doi.org/10.12989/cac.2016.18.1.001

Application of expert systems in prediction of flexural strength of cement mortars

Eyyup Gulbandilar*[1] and Yilmaz Kocak[2a]

[1]*Department of Computer Engineering, Faculty of Engineering and Architecture, Eskisehir Osmangazi University, Eskisehir, Turkey*
[2]*Department of Construction, Kutahya Vocational School of Technical Sciences, Dumlupinar University, Kutahya, Turkey*

(Received May 12, 2015, Revised December 14, 2015, Accepted March 8, 2016)

Abstract. In this study, an Artificial Neural Network (ANN) and Adaptive Network-based Fuzzy Inference Systems (ANFIS) prediction models for flexural strength of the cement mortars have been developed. For purpose of constructing this models, 12 different mixes with 144 specimens of the 2, 7, 28 and 90 days flexural strength experimental results of cement mortars containing pure Portland cement (PC), blast furnace slag (BFS), waste tire rubber powder (WTRP) and BFS+WTRP used in training and testing for ANN and ANFIS were gathered from the standard cement tests. The data used in the ANN and ANFIS models are arranged in a format of four input parameters that cover the Portland cement, BFS, WTRP and age of samples and an output parameter which is flexural strength of cement mortars. The ANN and ANFIS models have produced notable excellent outputs with higher coefficients of determination of R^2, RMS and MAPE. For the testing of dataset, the R^2, RMS and MAPE values for the ANN model were 0.9892, 0.1715 and 0.0212, respectively. Furthermore, the R^2, RMS and MAPE values for the ANFIS model were 0.9831, 0.1947 and 0.0270, respectively. As a result, in the models, the training and testing results indicated that experimental data can be estimated to a superior close extent by the ANN and ANFIS models.

Keywords: ANN; ANFIS; blast furnace slag; waste tire rubber powder; flexural strength

1. Introduction

With the advancement of industrial activity, the amount of industrial by-product waste materials such as fly ash, silica fume, blast furnace slag and waste tire rubber have continuously increased and the treatment and disposal of waste is a serious problem in the context of sustainability and environmental issues. Two of the industrial wastes are blast furnace slag and waste tire rubber.

Blast furnace slag is a by-product of the manufacture of pig iron from iron ore, limestone and coke. Slag is rapidly cooled by quenching to obtain an almost completely amorphous material.

∗Corresponding author, Ph. D., E-mail: egul50@gmail.com
[a]Senior author, Ph. D., E-mail: yilmaz.kocak@dpu.edu.tr

http://www.techno-press.org/?journal=cac&subpage=8 ISSN: 1598-8198 (Print), 1598-818X (Online)

Currently, there is high interest in the application of this alternative material because the production of slag cement reduces the CO_2 emissions (Crossin 2015). Furthermore, the use of blast furnace slag as a supplementary cementing material due to advantages such as high resistance to chloride penetration, sulfate attack and ASR, improved workability, pumpability and compaction characteristics for concrete placement, increased strength and durability, reduced permeability have become very common in modern cement and concrete technology (Siddiquea and Bennacer 2012, Deb *et al.* 2014, Atis and Bilim 2007, Dellinghausen *et al.* 2012, Teng *et al.* 2013, Zhu *et al.* 2012, Yung *et al.* 2013).

Large quantities of scrap tires are generated each year globally. In recent years, with an ever increasing number of scrap tires in the world, the disposal of used rubber tires has been a serious problem in environments. The ever increasing stockpile of waste rubber tires is a potential environmental hazard. One way of utilizing waste rubber tires is to recycle them. Concerning the reuse of recycled rubber in mortars and concrete, extensive studies have been conducted on used tires modified concrete and mortars. Results have indicated that rubberized concrete mixtures show lower density, increased toughness and ductility, higher impact resistance, lower compressive and splitting tensile strength, and more efficient sound insulation (Yilmaz and Degirmenci 2009, Al-Akhras and Smadi 2004, Eiras *et al.* 2014, Uygunoglu and Topcu 2010).

Because of these advantages, waste materials such as blast furnace slag (BFS) and waste tire rubber powder (WTRP) are used as supplementary cement and concrete material, or artificial pozzolan, in cement and concrete industry. In this industry, it causes losses in both time and financial costs for preparing the cement mortars and concretes by using various additives. By using various calculation methods, these losses are eliminated. While some researchers prefer statistical methods, other researchers prefer the expert systems. Artificial Neural Network (ANN) and fuzzy logic have become popular and have been used by many researchers to solve a wide variety of problems in civil engineering applications (Sakthivel *et al.* 2016, Motamedi *et al.* 2015, Behnood *et al.* 2015, Mansouri and Kisi 2015, Wang *et al.* 2015, Beycioğlu *et al.* 2015, Subasi 2009, Topcu and Saridemir 2008, Yaprak *et al.* 2013, Gulbandilar and Kocak 2013). On the other hand, Adaptive Neuro-Fuzzy Inference System (ANFIS) and multiple regression analysis are used in civil engineering to perform predictions. Furthermore, expert systems compared to the multiple regression analysis method yield better results (Komleh and Maghsoudi 2015).

In this study, we aimed to develop a model to evaluate the effect of BFS and WTRP on flexural strength of cement mortars by using ANN and ANFIS. Therefore, it may lead to decrease of the losses in labor, time and financial costs. For purpose of constructing this model, 12 different mixes with 144 specimens of the 2, 7, 28 and 90 days flexural strength experimental results of cement mortars containing Portland cement (PC), BFS, WTRP, BFS+WTRP used in training and testing for ANN and ANFIS were gathered from the standard cement tests. The models was trained with 120 data of experimental results. The ANN and ANFIS models had four input parameters and one output parameter. The obtained results from flexural strength tests were compared with predicted results.

2. Experimental study

The materials used in this study were Portland cement (PC), blast furnace slag (BFS), waste tire rubber powder (WTRP), standard aggregate and water. The PC was CEM I 42.5 R in accordance with TS EN 197-1 (TS EN 197-1 2012), which was provided from SET Istanbul Ambarli Cement

Table 1 Codes and mix proportions of blended cements

Cement type	PC, g	PC, %	BFS, g	BFS, %	WTRP, g	WTRP, %
C1	450	100	0	0	0	0
C2	427.5	95	22.5	5	0	0
C3	405	90	45	10	0	0
C4	382.5	85	67.5	15	0	0
C5	360	80	90	20	0	0
C6	438.75	97.5	0	0	11.25	2.5
C7	427.5	95	0	0	22.5	5
C8	427.5	95	11.25	2.5	11.25	2.5
C9	405	90	33.75	7.5	11.25	2.5
C10	405	90	22.5	5	22.5	5
C11	405	85	45	10	22.5	5
C12	405	80	67.5	15	22.5	5

Table 2 Chemical compositions of used blended cements

Materials	C1, %	C2, %	C3, %	C4, %	C5, %	C6, %	C7, %	C8, %	C9, %	C10, %	C11, %	C12, %
Chemical composition, %												
SiO_2	19.84	20.20	20.89	22.00	23.43	19.67	19.66	19.85	21.36	20.72	21.37	22.18
Al_2O_3	5.16	5.47	5.85	6.45	7.24	5.16	5.17	5.30	6.03	5.70	6.09	6.52
Fe_2O_3	2.62	2.57	2.53	2.44	2.30	2.66	2.70	2.63	2.55	2.63	2.55	2.51
CaO	63.48	62.35	61.32	59.53	57.33	62.44	61.25	61.71	59.93	59.95	58.93	57.37
MgO	1.11	1.33	1.60	2.04	2.61	1.14	1.16	1.25	1.74	1.54	1.81	2.13
SO_3	2.81	2.81	2.64	2.56	1.98	1.79	0.82	1.95	1.20	0.33	0.90	0.22
K_2O	0.78	0.81	0.79	0.80	0.82	0.79	0.80	0.79	0.81	0.81	0.82	0.83
Na_2O	0.41	0.43	0.44	0.46	0.47	0.43	0.46	0.44	0.54	0.54	0.54	0.56

Plant which is used as reference. BFS and WTRP were participated in the production of this cement as minor additional components. BFS was obtained from the Eregli Iron and Steel Plant in Zonguldak (Turkey). WTRP was obtained from a Commercial Business in Ankara (Turkey). WTRP, in the bottom during the making various grades and sizes of granules obtained from waste tires in very fine powder, and was obtained by sieving 125 μm sieve. Standard aggregate which was produced by SET Trakya Cement industry in accordance with TS EN 196-1 (TS EN 196-1 2009) and city water supply of Istanbul Province Buyukcekmece District were used in the preparation in the cement mortars.

In the study, a total of twelve different mixtures are obtained with PC being the reference. The amount of PC is reduced by 5, 10, 15 and 20% by weight being substituted by the same amount of BFS. Similarly, the amount of WTRP substitution is 2.5 and 5% by weight. Besides, in order to investigate the properties of ternary mixtures, the amount of PC is reduced by 2.5+2.5%, 7.5+2.5%, 5+5%, 10+5%, 15+5% by weight being substituted by the same amount of BFS and WTRP, respectively.

The produced reference and blended cement codes and mix proportions are given in Table 1. This study is limited to cement types as shown in Table 1.

Table 3 Physical specifications of materials

Mixtures	Range dimension (over sieve), %			Specific gravity, g/cm^3	Blaine, cm^2/g
	>45 μm	>90 μm	>200 μm		
PC	4.7	0.3	0.0	3.15	3504
WTRP	45.4	17.9	2.2	1.70	2404
BFS	60.9	46.0	25.5	2.88	1848
C1	6.2	0.2	0	3.15	3483
C2	7.8	1.3	0	3.16	3578
C3	10.4	3.7	0	3.15	3505
C4	14.0	7.1	0.5	3.11	3233
C5	10.9	3.9	0	3.10	3040
C6	7.3	0.5	0	3.11	3667
C7	7.5	0.5	0	2.88	3341
C8	8.3	1.7	0	3.09	3547
C9	11.5	4.0	0	3.06	3352
C10	12.0	3.9	0	3.08	3354
C11	12.1	4.2	0	2.98	3326
C12	23.9	13.8	1.2	2.99	3009

Chemical analyses of cements were performed on ARL 8680 X-ray workstation. Analysis results depicting the chemical compositions of the blended cements were given in Table 2.

Surface areas were determined as Blaine values by Toni Technik 6565 Blaine and specific weights were determined by Quantachrome MVP–3. Physical specifications of cement, BFS and WTRP were given in Table 3.

In the preparation of cement mortar mixtures for flexural strength experiments, 450 g of PC, 1350 g of standard sand and 225 ml of water are used in each mortar mixture according to TS EN 196-1 and mixed in mortar mixer machine. Prepared cement mortars are poured into three-segmented rectangular prism moulds of size 40×40×160 mm. Prepared samples are waited in the laboratory for 24 hours. At the end of 24-hour period, the samples are taken out of the moulds and waited in water pools to get cured and prepared for the flexural strength experiments. Flexural strength of each cement mortar is measured at the end of 2, 7, 28 and 90 days using Atom Technik device.

3. Artificial neural network

Artificial neural network **(**ANN) consisted of an arbitrary number of simple elements called neurons. Neurons in ANN are, as similar in human brain, interconnected (Adhikary and Mutsuyoshi 2006). ANN represents simplified methods of a human brain and uses new methods to solve problems rather than conventional methods with traditional computations which have difficult solution procedures (Trtnik *et al.* 2009). Generally, ANN is consisted of an input layer of

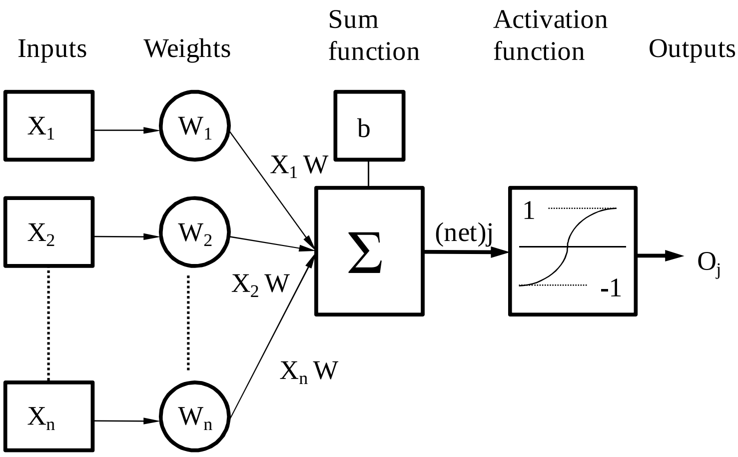


Fig. 1 The artificial neuron model

neurons, one or more hidden layers of neurons and output layer of neurons. The neighboring layers are fully interconnected by weight. The input layer neurons receive information from the outside environment and transmit them to the neurons of the hidden layer without performing any calculation. Layers between the input and output layers are called hidden layers and may contain a large number of hidden processing units. All problems, which can be solved by a perceptron can be solved with only one hidden layer, but it is sometimes more efficient to use two hidden layers. Finally, the output layer neurons produce the network predictions to the outside world (Demir 2008).

Fig. 1 clearly illustrates the typical neural network which is composed of five main parts such as; inputs, weights, sum function, activation function and outputs (Topcu *et al.* 2008, Parichatprecha and Nimityongskul 2009).

The input of a neuron comes from another neuron and it is obtained by multiplying the output of the connected neuron by the synaptic strength of the connection between them. The weighted sums of the input components $(\text{net})_j$ are calculated by using Eq. (1) below:

$$(\text{net})_j = \sum_{i=1}^{n} w_{ij} o_i + b \tag{1}$$

Where (net)j is the weighted sum of the j_{th} neuron for the input received from the preceding layer with n neurons, w_{ij} is the weight between the j_{th} neuron in the preceding layer, o_i is the output of the i_{th} neuron in the preceding layer and b is a fix value as an internal addition (Topcu *et al.* 2008). Activation function is a function that processes the net input obtained from sum function and determines the neuron output. In general for multilayer feed forward models as the activation function $(f\ (\text{net})_j)$ sigmoid activation function is used. The output of the j_{th} neuron $(\text{out})_j$ is computed using Eq. (2) with a sigmoid activation function as follows (Topcu *et al.* 2009)

$$o_j = f(\text{net})_j = \frac{1}{1 + e^{-\alpha(\text{net})_j}} \tag{2}$$

Where α is constant used to control the slope of the semi-linear region. The sigmoid

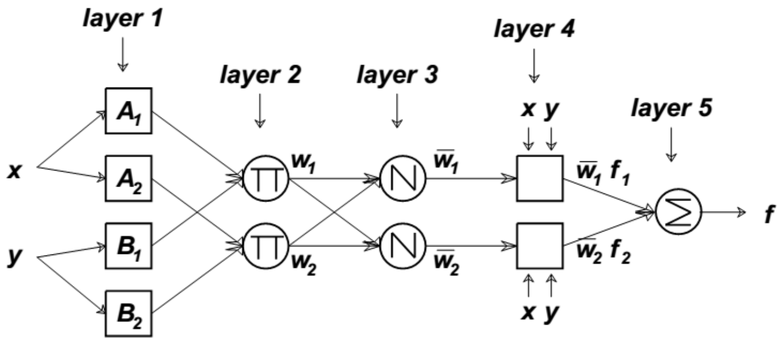


Fig. 2 Equivalent ANFIS architecture

nonlinearity activates in every layer except in the input layer. The sigmoid function represented by Eq. (2) gives outputs in (0, 1). If it desired, the outputs of this function can be adjusted to (-1, 1) interval. As the sigmoid processor represents a continuous function it is particularly used in non-linear descriptions. Because its derivatives can be determined easily with regard to the parameters within $(net)_j$ variable (Topcu *et al.* 2009).

4. Adaptive neural fuzzy inference systems

Adaptive Neural Fuzzy Inference Systems (ANFIS) is a hybrid system which is including both neuronal network and fuzzy inference systems. While fuzzy inference in this hybrid system uses into account for the imprecision and uncertainty, the neuronal network uses for the adaptability. The hybrid systems generally named the Sugeno fuzzy model. Takagi, Sugeno, and Kang advised this model which is producing fuzzy rules from an input-output data set. A typical fuzzy rule has the format

If x is A and y is B then z = f(x,y)

Where *A* and *B* are fuzzy sets in the antecedent; $z=f(x,y)$ is a crisp function in the consequent. Usually $f(x,y)$ is a polynomial in the input variables *x* and *y*. When $f(x,y)$ is a first-order polynomial, this model determined the first-order Sugeno fuzzy model. If *f* is a constant, it is zero-order Sugeno fuzzy model. Consider a first-order Sugeno fuzzy inference system which contains two fuzzy *If-then* rules

Rule1: If x is A_1 *and y is* B_1 *, then* $f_1= p_1 x+ q_1 y +r_1$
Rule 2: If x is A_2 *and y is* B_2 *, then* $f_2= p_2 x+ q_2 y+ r_2$

In this inference system, the output of each rule is a linear combination of the input variables added by a constant term. The final output is the weighted average ($\overline{w_i}$) of each rule's output (Aali *et al.* 2009, Jang 1996).

The equivalent ANFIS architecture is shown in Figure, where node within the same layer perform functions of the same type, as detailed below. (Note that O_i^j denotes the output of the *i*-th node in *j*-th layer.)

Layer 1 (Fuzzification layer): Every node *i* in this layer is an adaptive node with node function

$$O_i^1 = A_i(x), \qquad for \quad i = 1,2, or$$
$$O_i^1 = B_{i-2}(y), \qquad for \quad i = 3,4$$

where *x* or *y* is the input to the *i* th node, and A_i or B_{i-2} is a linguistic label such as *tall*, *short*. In other words, O_i^j is the membership degree of a fuzzy set A or B.

$$O_i^j = \mu A_i(x) = \frac{1}{1 + \left[(x - c_i)/a_i\right]^{2b_i}} \tag{3}$$

where {a_i, b_i, c_i} is the parameter set. As the values of these parameters change, the bell-shaped function varies accordingly, thus exhibiting various forms of membership functions on linguistic label A_i. Parameters in this layer are referred to as premise parameters. The outputs of this layer are the membership values of the premise part.

Layer 2 (Rule inference layer): Each node in this layer calculates the firing strength of a rule via multiplication

$$O_i^2 = \mu A_i(x).\mu B_i(y) \qquad i = 1,2,... \tag{4}$$

where, each node output represents the firing strength of a rule.

Layer 3 (Normalization layer): Node *i* in this layer calculates the ratio of the *i*-th rule's firing strength to the total of all firing strengths

$$O_i^3 = \overline{w}_i = \frac{w_i}{w_1 + w_2} \qquad i = 1,2,... \tag{5}$$

The outputs of this layer are called normalized firing strengths.

Layer 4 (Consequent layer): Node *i* in this layer compute the contribution of *i*-th rule toward the overall output with the following no de function

$$O_i^4 = \overline{w}_i . f_i = \overline{w}_i . \left(p_i . x + q_i y + r_i\right) \tag{6}$$

where w_i is the output of layer 3, and {p_i, q_i, r_i} is the parameter set. Parameters in this layer are referred to as the consequent parameters.

Layer 5 (Output layer): This layer's single fixed node labeled $\sum$ computes the final output as the summation of all incoming signals.

$$O_i^5 = overall\ output = \sum_i \overline{w}_i \cdot f_i = \frac{\sum_i w_i \cdot f_i}{\sum_i w_i} \tag{7}$$

The basic learning rule of ANFIS is the backpropagation gradient descent, which calculates error signals (the derivative of the squared error with respect to each node's output) recursively from the output layer backward to the input nodes. This learning rule is exactly the same as the

Table 4 The input and output quantities used in ANN and ANFIS models

		Data used in training and testing the model	
		Minimum	Maximum
Input variable	Age of samples, days	2	90
	PC, g	360	450
	BFS, g	0	90
	WTRP, g	0	11.25
Output variable	Flexural strength, MPa	3	8.2

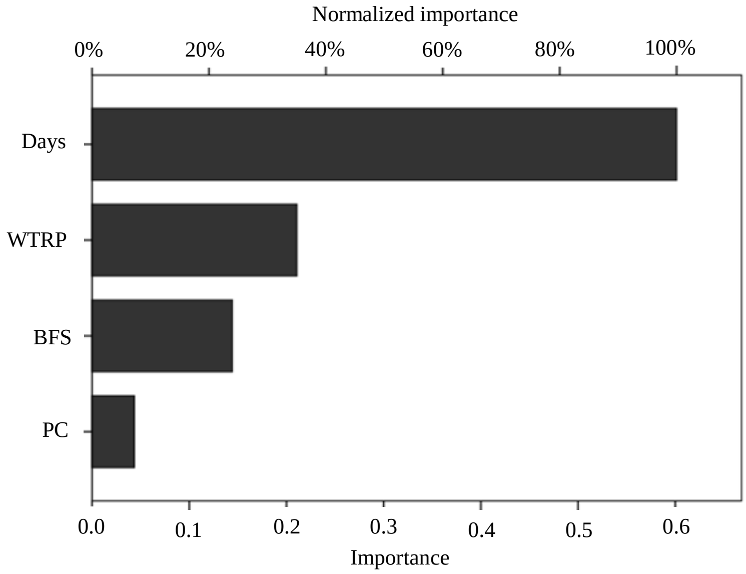


Fig. 3 The importance of sensitivity for input variables

backpropagation learning rule used in the common feedforward neural networks.

5. Experimental design and model parameters

In training and testing of the ANN and ANFIS the age of samples, PC, BFS and WTRP were entered as input; while flexural strength values of cement mortars were used as output (Table 4). The comprehensive sensitivity analysis of input variables for output variable was determined using SPSS 20.0 software package (Fig. 3). The importance of sensitivity for Days, WTRP, BFS and PC as input variables were 0.601, 0.211, 0.144 and 0.043, respectively. We have used all the input variables in our study since the results of the analysis were almost identical.

In the ANN and ANFIS models, 120 of the experimental data were used for the training of the models and other 24 experimental data were used for testing the trained model.

The designed ANN consisted of feed-forward back propagation, four hidden layers, training function (Levenberg-Marquardt), adaptation learning function (learngdm), transfer function (tansig) and performance function (MSE-mean squared error) as demonstrated in Fig. 4. The

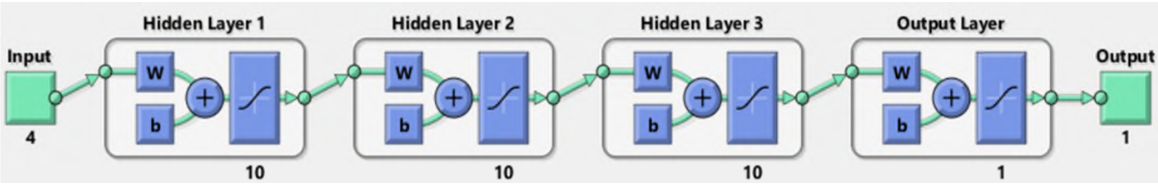


Fig. 4 The architecture used in the neural network model for flexural strength

Table 5 The values of parameters used in models

Parameters	ANN
Number of input layer neurons	4
Number of hidden layer	4
Number of first hidden layer neurons	10
Number of second hidden layer neurons	10
Number of 3 hidden layer neurons	10
Number of 4 hidden layer neurons	10
Number of output layer neuron	1
Error after learning	3.66×10^{-3}
Learning cycle	16

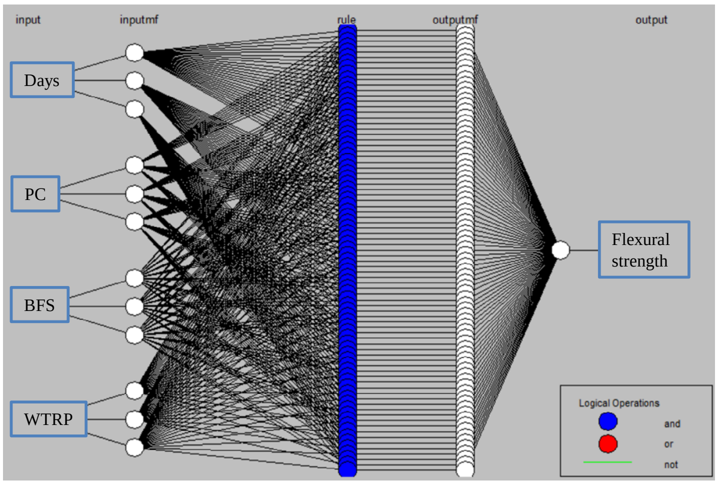


Fig. 5 General structure of the model

neurons used in the system are 10 and 1, in the first, second, third and the fourth layers, respectively. Momentum rate and learning rate values were determined and the model was trained through iterations. The parameter values obtained from the multilayer feed-forward neural network model were given in Table 5.

ANFIS model developed in this research has four inputs that the age of samples (days), PC, BFS and WTRP and an output fluxural strength of the cement mortars (Fig. 5). In the model, after experimenting different learning algorithms with different epochs, best correlations was found through hybrid learning algorithm and 1500 epochs. In the model 3 ‘‘gaussmf’’ membership functions were selected for the age of samples (days), PC, BFS and WTRP. Membership functions of inputs are displayed in Fig. 6.

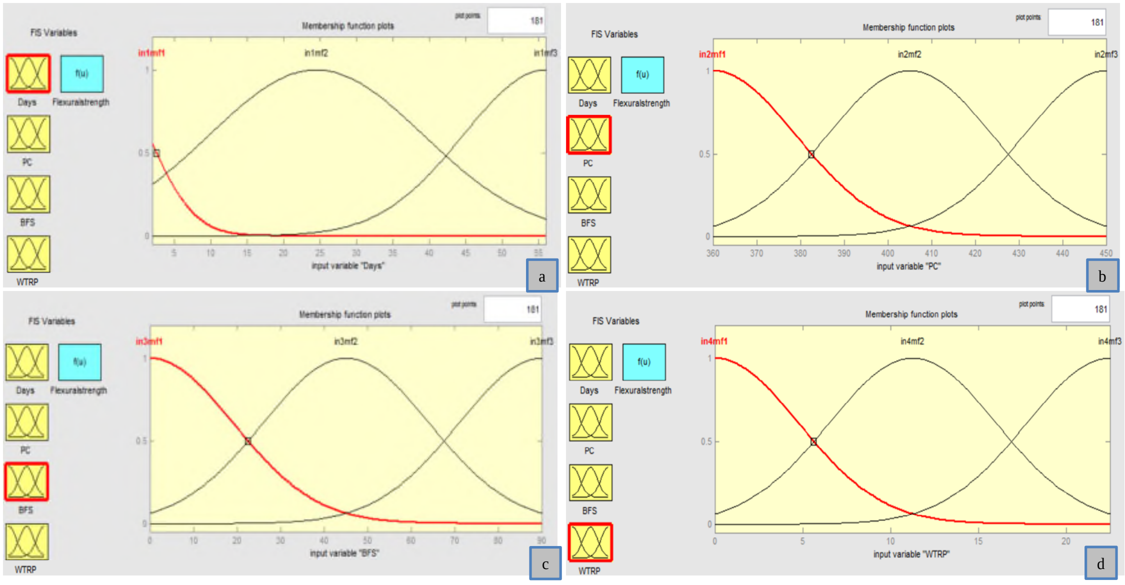


Fig. 6 Membership functions of input variables

6. Results and discussion

In this study, the values of flexural strength were modeled using ANN and ANFIS. In the training and testing of ANN and ANFIS model from experimental data are used. In the ANN model, 120 data of experiment results were used for training whereas 24 ones were employed for testing.

The network models tried to be compared according to the absolute fraction of variance (R^2), mean absolute percentage error (MAPE) and a root-mean squared (RMS) error criteria. These criteria are defined by Eqs. (8), (9) and (10), respectively (Ozcan *et al.* 2009).

$$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left|t_i - o_i\right|^2} \tag{8}$$

$$R^2 = 1 - \left(\frac{\sum_{i=1}^{N}(t_i - o_i)^2}{\sum_{i=1}^{N}(o_i)^2}\right) \tag{9}$$

$$\mathrm{MAPE} = \frac{1}{N}\sum_{i=1}^{N}\left|\left(\frac{t_i - o_i}{o_i}\right)\right| * 100 \tag{10}$$

here ***t*** is the target value, ***o*** is the network output value, ***N*** is the total number of pattern.

In the training and testing of ANN and ANFIS models from experimental data are used. In the

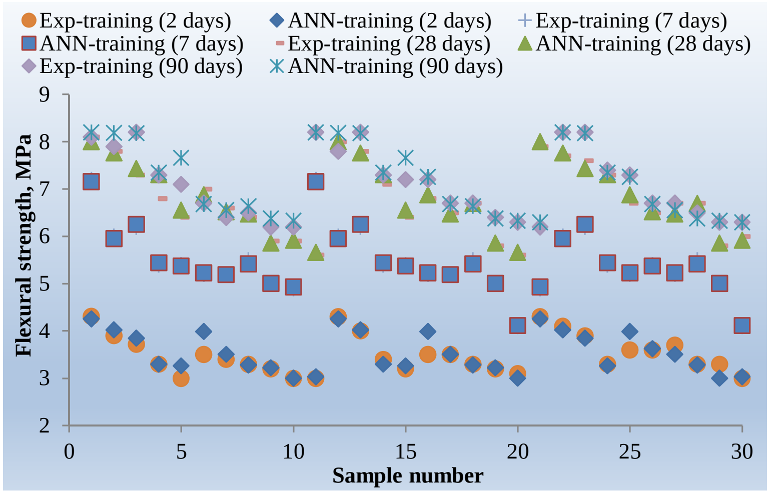
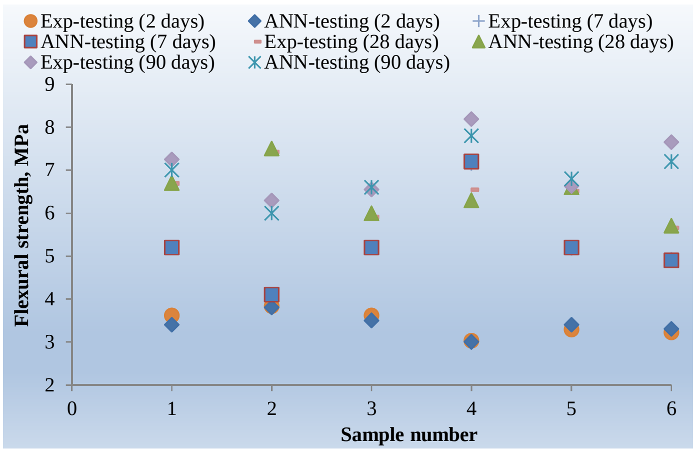


Fig. 7 Comparison of flexural strength experimental and training results of ANN model with sample number



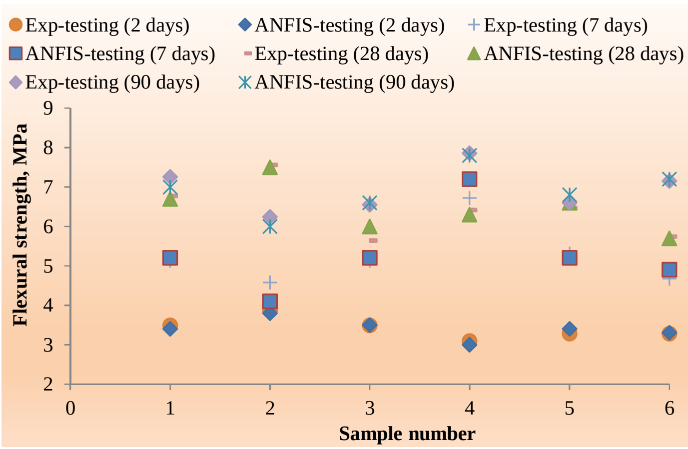


Fig. 8 Comparison of flexural strength experimental and testing results of ANN and ANFIS models with sample number

Table 6 Comparison of flexural strength experimental results with testing results obtained from ANN and ANFIS

Data used in the model construction				Flexural strength, MPa		
Days	PC, g	BFS, g	WTRP, g	Exp.	ANN	ANFIS
2	427.5	0	22.5	3.40	3.62	3.49
2	405	45	0	3.80	3.84	3.87
2	427.5	0	22.5	3.50	3.62	3.49
2	405	67.5	22.5	3.00	3.03	3.09
2	382.5	67.5	0	3.40	3.29	3.28
2	405	22.5	22.5	3.30	3.22	3.28
7	360	90	0	5.20	5.21	5.13
7	405	45	22.5	4.10	4.10	4.58
7	360	90	0	5.20	5.21	5.13
7	450	0	0	7.20	7.15	6.72
7	427.5	11.25	11.25	5.20	5.17	5.31
7	405	67.5	22.5	4.90	4.92	4.68
28	405	33.75	11.25	6.70	6.69	6.77
28	405	45	0	7.50	7.43	7.56
28	405	45	22.5	6.00	5.91	5.64
28	360	90	0	6.30	6.54	6.42
28	427.5	0	22.5	6.60	6.51	6.46
28	405	67.5	22.5	5.70	5.65	5.74
90	438.75	0	11.25	7.00	7.25	7.25
90	405	67.5	22.5	6.00	6.29	6.24
90	427.5	11.25	11.25	6.60	6.55	6.55
90	427.5	22.5	0	7.80	8.19	7.86
90	405	33.75	11.25	6.80	6.63	6.6
90	360	90	0	7.20	7.66	7.15

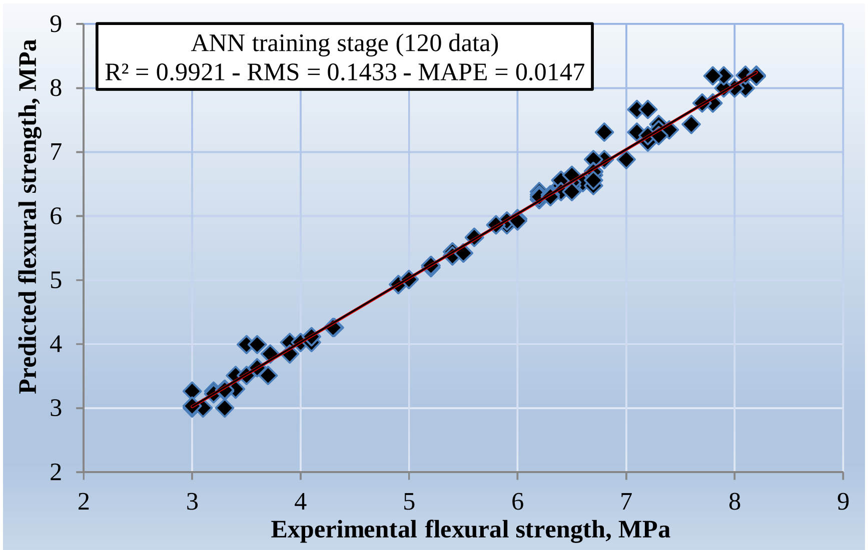


Fig. 9 Comparison of flexural strength experimental results with training results of ANN model

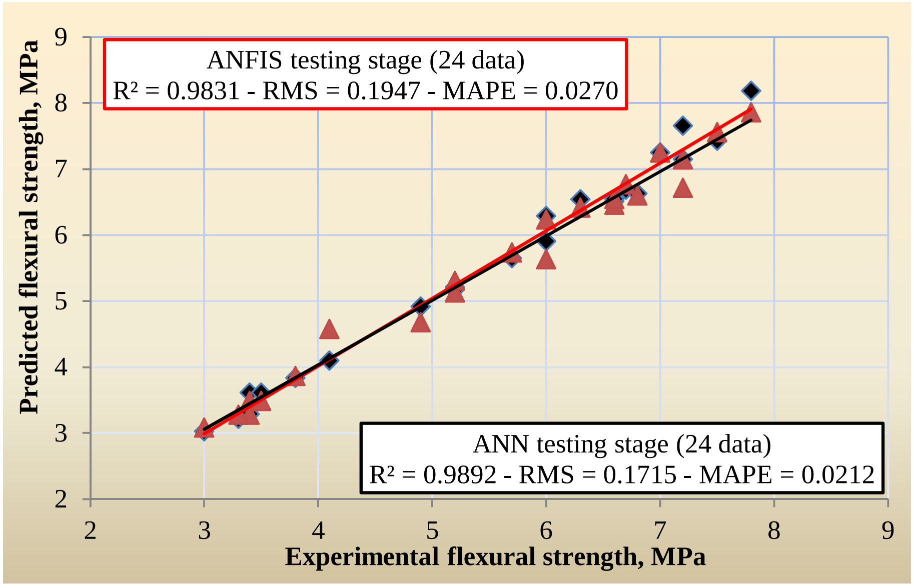


Fig. 10 Comparison of flexural strength experimental results with testing results of ANN (♦) and ANFIS models

Table 7 The flexural strength statistical values of proposed ANN and ANFIS models

Statistical parameters	ANN		ANFIS
	Training set	Testing set	Testing set
R^2	0.9921	0.9892	0.9831
RMS	0.1433	0.1715	0.1947
MAPE	0.0147	0.0212	0.0270

ANN model, 120 data of experiment results were used for training whereas 24 data were employed for testing. Sample number and experimental results with training results obtained from ANN model were given in Fig. 7.

Sample number and experimental results with training and testing results obtained from ANN and ANFIS models were given in Fig. 8.

Inputs values and experimental results with testing results obtained from ANN and ANFIS models were given in Table 6.

All results obtained from experimental studies and predicted by using the training and testing results of ANN and ANFIS models, for 2, 7, 28 and 90 days flexural strength were given in Fig. 9 and 10, respectively.

The linear least square fit line, its equation and the R^2 values were shown in these figures for the training and testing data. As it is visible in Fig. 9 and 10 the values obtained from the training and testing in ANN and ANFIS models are very closer to the experimental results. The result of testing phase in Fig. 9 and 10 shows that the ANN and ANFIS models are capable of generalizing between input and output variables with reasonably good predictions.

The statistical values for all the station such as RMS, R^2 and MAPE, both training and testing, were given in Table 7.

While the statistical values of R^2, RMS and MAPE from training in the ANN model were found as 0.9921, 0.1433 and 0.0147, respectively, these values were found in testing as 0.9892, 0.1715 and 0.0212, respectively. While the statistical values of R^2, RMS and MAPE from testing in the ANFIS model were found as 0.9831, 0.1947 and 0.0270, respectively. All of the statistical values in Table 7 show that the proposed ANN and ANFIS models are suitable and predict the 2, 7, 28 and 90 days flexural strength values very close to the experimental values.

7. Conclusions

In this study, ANN and ANFIS were used for the prediction the 2, 7, 28 and 90 days flexural strength values of cement mortars containing PC, BFS, WTRP and BFS+WTRP. While developing the two models, 120 experimental data (randomly selected) used for training and 24 experimental data (the residual data) used for testing the models. While developing ANN and ANFIS models, different learning algorithms with different epochs were experimented to define the model which has best potential estimation ability to predict experimental results. After finding the best ANN and ANFIS models, results of ANN, ANFIS and experimental results were compared. For comparing the ANN, ANFIS and experimental results, R^2, RMS and MAPE statistics were used as evaluation criteria. When comparing the prediction and the experimental values in the training stage R^2, RMS and MAPE were found as 0.9921, 0.1433 and 0.0147 for ANN model, respectively. Similarly comparisons were done at the test stage and R^2, RMS and MAPE were found as 0.9892, 0.1715 and 0.0212 for ANN model 0.9831, 0.1947 and 0.0270 for ANFIS model respectively. According to the obtained results, the flexural strength values are very close to the experimental data obtained from training and testing for both ANN and ANFIS models. The statistical parameter values of R^2, RMS and MAPE that calculated for comparing experimental data with ANN and ANFIS models results have shown obviously this situation.

As a result, flexural strength values of cement mortars containing PC, BFS, WTRP and BFS+WTRP can be predicted in the ANN and ANFIS models in a quite short period of time with tiny error rates. The conclusions have shown that ANN and ANFIS systems are practicable methods for predicting flexural strength values of cement mortars containing PC, BFS, WTRP and BFS+WTRP. Furthermore, these systems can reduce losses in both elapsed time and financial costs during the preparation of the cement mortars and concretes by exploiting various additives. In the future, new studies can be made by removing limitations such as the cement type prepared with various mineral additives.

Acknowledgement

The authors would like to thank Duzce University Scientific Research Unit for providing financial support for this research (Project Code Number: 2011.03.HD.011). They would also like to thank SET Ambarli Cement Plant executives and the staff for their invaluable contributions on this study.

References

Aali, K.A., Parsinejad, M. and Rahmani, B. (2009), “Estimation of saturation percentage of soil using multiple regression, ANN, and ANFIS techniques”, *Comput. Inform. Sci.,* **2**(3), 127-136.

Adhikary, B.B. and Mutsuyoshi, H. (2006), “Prediction of shear strength of steel fiber RC beams using neural networks”, *Constr. Build. Mater.*, **20**(9), 801-811.

Al-Akhras, N.M. and Smadi, M.M. (2004), “Properties of tire rubber ash mortar”, *Cement Concrete Compos.*, **26**, 821-826.

Atiş, C.D. and Bilim, C. (2007), “Wet and dry cured compressive strength of concrete containing ground granulated blast-furnace slag”, *Build. Envir.*, **42**(8), 3060-3065.

Behnood, A., Verian, K.P. and Gharehveran, M.M. (2015), “Evaluation of the splitting tensile strength in plain and steel fiber-reinforced concrete based on the compressive strength”, *Constr. Build. Mater.*, **98**, 519-529.

Beycioglu, A., Emiroglu, M., Kocak, Y. and Subasi, S. (2015), “Analyzing the compressive strength of clinker mortars using approximate reasoning approaches-ANN vs MLR”, *Comput. Concrete*, **15**(1), 89-101.

Crossin, E. (2015), “The greenhouse gas implications of using ground granulated blast furnace slag as a cement substitute”, *J.Clean. Product.*, **95**, 101-108.

Deb, P.S., Nath, P. and Sarker, P.K. (2014), “The effects of ground granulated blast-furnace slag blending with fly ash and activator content on the workability and strength properties of geopolymer concrete cured at ambient temperature”, *Mater. Des.*, **62**, 32-39.

Dellinghausen L.M., Gastaldini A.L.G., Vanzin F.J. and Veiga K.K. (2012), “Total shrinkage, oxygen permeability, and chloride ion penetration in concrete made with white Portland cement and blast-furnace slag”, *Constr. Build. Mater.*, **37**, 652-659.

Demir, F. (2008), “Prediction of elastic modulus of normal and high strength concrete by artificial neural network”, *Constr. Build. Mater.*, **22**(7), 1428-1435.

Eiras, J.N., Segovia, F., Borrachero, M.V., Monzó, J., Bonilla, M. and Payá, J. (2014), “Physical and mechanical properties of foamed Portland cement composite containing crumb rubber from worn tires”, *Mater. Des.*, **59**, 550-557.

Gulbandilar, E. and Kocak, Y. (2013), “Prediction the effects of fly ash and silica fume on the setting time of Portland cement with fuzzy logic”, *Neur. Comput. Appl.*, **22**, 1485-1491.

Jang, J.S.R. (1996), “Input selection for ANFIS learning, Fuzzy Systems”, *Proceedings of the Fifth IEEE International Conference on*, New Orleans, September.

Komleh, H.E and Maghsoudi, A.A. (2015), “Prediction of curvature ductility factor for FRP strengthened RHSC beams using ANFIS and regression models”, *Comput. Concrete*, **16**(3), 399-414.

Mansouri, I. and Kisi, O. (2015), “Prediction of debonding strength for masonry elements retrofitted with FRP composites using neuro fuzzy and neural network approaches”, *Compos.: Part B*, **70**, 247-255.

Motamedi, S., Shamshirband, S., Petković, D. and Hashim, R. (2015), “Application of adaptive neuro-fuzzy technique to predict the unconfined compressive strength of PFA-sand-cement mixture”, *Powder Tech.*, **278**, 278-285.

Ozcan, F., Atis, C.D., Karahan, O., Uncuoglu, E. and Tanyildizi, H. (2009), “Comparison of artificial neural network and fuzzy logic models for prediction of long-term compressive strength of silica fume concrete”, *Adv. Eng. Softw.*, **40**, 856-863.

Parichatprecha, R. and Nimityongskul, P. (2009), “Analysis of durability of high performance concrete using artificial neural Networks”, *Constr. Build. Mater.*, **23**, 910-917.

Sakthivel, P.B., Ravichandran, A. and Alagumurthi, N. (2016), “Modeling and pediction of flexural strength of hybrid mesh and fiber reinforced cement-based composites using Artificial Neural Network (ANN)”, *Int. J. Geomate*, **10**(1), 1623-1635.

Siddiquea, R. and Bennacer, R. (2012), “Use of iron and steel industry by-product (GGBS) in cement paste and mortar. Resources”, *Conserv. Recy.*, **69**, 29-34.

Subasi, S. (2009), “Prediction of mechanical properties of cement containing class C fly ash by using artificial neural network and regression technique”, *Sci. Res. Essay*, **4**(4), 289-297.

Teng, S., Lim, T.Y.D. and Divsholi, B.S. (2013), “Durability and mechanical properties of high strength concrete incorporating ultra fine ground granulated blast-furnace slag”, *Constr. Build. Mater.*, **40**, 875-881.

Topcu, İ.B. and Saridemir, M. (2008), "Prediction of compressive strength of concrete containing fly ash using artificial neural networks and fuzzy logic", *Comput. Mater. Sci.*, **41**, 305-311.
Topcu, İ.B., Karakurt, C. and Saridemir, M. (2008), "Predicting the strength development of cements produced with different pozzolans by neural network and fuzzy logic", *Mater. Des.*, **29**(10), 1986-1991.
Topcu, İ.B., Saridemir, M., Ozcan, F. and Severcan, M.H. (2009), "Prediction of long-term effects of GGBFS on compressive strength of concrete by artificial neural networks and fuzzy logic", *Constr. Build. Mater.*, **23**, 1279-1286.
Trtnik, G., Kavčič, F. and Turk, G. (2009), "Prediction of concrete strength using ultrasonic pulse velocity and artificial neural networks", *Ultrasonics,* **49**(1), 53-60.
TS EN 196-1 (2009), "Methods of testing cement-Part 1: Determination of strength", Turkish Standards, Ankara, Turkey.
TS EN 197-1 (2012), "Cement- Part 1: Compositions and conformity criteria for common cements", Turkish Standards, Ankara, Turkey.
Uygunoğlu, T. and Topçu, İ.B. (2010), "The role of scrap rubber particles on the drying shrinkage and mechanical properties of self-consolidating mortars", *Constr. Build. Mater.*, **24**(7), 1141-1150.
Wang, B., Man, T. and Jin, H. (2015), "Prediction of expansion behavior of self-stressing concrete by artificial neural networks and fuzzy inference systems", *Constr. Build. Mater.*, **84**, 184-191.
Yaprak, H., Karaci, A. and Demir, İ. (2013), "Prediction of the effect of varying cure conditions and w/c ratio on the compressive strength of concrete using artificial neural networks", *Neur. Comput. Appl.*, **22**, 133-141.
Yilmaz, A. and Degirmenci, N. (2009), "Possibility of using waste tire rubber and fly ash with Portland cement as construction materials", *Waste Manage.*, **29**, 1541-1546.
Yung, W.H., Yung, L.C. and Hua, L.H. (2013), "A study of the durability properties of waste tire rubber applied to self-compacting concrete", *Constr. Build. Mater.*, **41**, 665-672.
Zhu, J., Zhong, Q., Chen, G. and Li, D. (2012), "Effect of particlesize of blast furnace slag on properties of portland cement", *Procedia Eng.*, **27**, 231-236.

CC