**Computers and Concrete**, *Vol. 21, No. 1 (2018) 21-30*
DOI: https://doi.org/10.12989/cac.2018.21.1.021


# Compressive strength estimation of concrete containing zeolite and diatomite: An expert system implementation

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*(Received March 20, 2017, Revised May 17, 2017, Accepted September 21, 2017)*

**Abstract.** In this study, we analyze the behavior of concrete which contains zeolite and diatomite. In order to achieve the goal, we utilize expert system methods. The utilized methods are artificial neural network and adaptive network-based fuzzy inference systems. In this respect, we exploit seven different mixes of concrete. The concrete mixes contain zeolite, diatomite, mixture of zeolite and diatomite. All seven concrete mixes are exposed to 28, 56 and 90 days' compressive strength experiments with 63 specimens. The results of the compressive strength experiments are used as input data during the training and testing of expert system methods. In terms of artificial neural network and adaptive network-based fuzzy models, data format comprises seven input parameters, which are; the age of samples (days), amount of Portland cement, zeolite, diatomite, aggregate, water and hyper plasticizer. On the other hand, the output parameter is defined as the compressive strength of concrete. In the models, training and testing results have concluded that both expert system model yield thrilling medium to predict the compressive strength of concrete containing zeolite and diatomite.

**Keywords:** expert systems; compressive strength; concrete; zeolite; diatomite

## 1. Introduction

Concrete is one of the most frequently used artificial construction material in construction technology. It is a composite material that consists of mixtures of cement, fine aggregate, coarse aggregate, water. Nowadays, most of the concretes are containing chemical admixtures and supplementary cementitious materials (Erdogan 2010, Neville 2006).

Supplementary cementitious materials, SCM, are some of the most important components of concrete. Due to economic and ecological factors, trass (Kocak *et al.* 2010), zeolite (Kocak *et al.* 2013), diatomite (Kocak and Savas 2016, Gerengi *et al.* 2013), metakaolin (Kelestemur and Demirel 2010, Subasi and Emiroglu 2015), pumice (Yildiz *et al.* 2010), fly ash (Kocak and Nas 2014, Zhengqi 2016), blast furnace slag (Zhu *et al.* 2012, Zhao *et al.* 2015), and silica fume (Okoye *et al.* 2016, Kocak 2010) are intensely used in the concrete technology. Some characteristics such as strength, durability and low permeability expected from good concrete are closely related not only to mix proportions but also to concrete properties. Zeolite and diatomite are natural mineral materials, that abundant in Turkey.

Zeolite, allophones type of morphology and consist of alkali and alkaline-earth cations. Zeolites keeps water molecules in their canals, which make it as a peculiar and decent mineral (Canpolat 2002, Serbest 1999). In terms of diatomite, it is a type of diatomite that is composed of the fossilized siliceous shell of the microscopic single-celled alga. The diatomite possesses the structural properties of amorphous silica. There are approximately fifteen thousand variations of diatomites exist in the nature. In general, the morphology is similar to the round tray or a long fish. High water absorption rate is another characteristic of this cellular material, and 70-90% of the diatomite is composed of $SiO_2$ (Aruntas and Tokyay 1996).

Contribution of zeolites and diatomite's on the compressive strength analysis of concrete can be observed in laboratory experiments. However, laboratory experiments would require financial cost due to material and energy prices. In addition, laboratory analysis takes decent amount of duration. In order to increase efficiency, novel computer based analysis approaches can be used.

Recently, common expert systems studies have been exploited to solve a wide variety of problems in civil engineering applications. One of the prominent expert system study used regression and artificial neural networks and introduced mathematical correlations among input and output dataset (Suzuki 2011). Other major studies implemented efficient expert system approaches such as fuzzy logic, adaptive fuzzy inference, genetic algorithms and decision trees (Behnood *et al.* 2015, Behnood *et al.* 2017, Velay-Lizancos *et al.* 2017). These studies developed clustering, classification and estimation utilities that extract

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

Table 1 The chemical properties of PC, diatomite and zeolite

| Materials | PC | Diatomite | Zeolite |
|---|---|---|---|
| Chemical composition, wt.% | | | |
| $SiO_2$ | 18.68 | 79.56 | 68.85 |
| $Al_2O_3$ | 4.67 | 6.54 | 11.71 |
| $Fe_2O_3$ | 3.53 | 2.76 | 1.29 |
| CaO | 64.56 | 2.45 | 3.97 |
| MgO | 0.98 | 0.79 | 1.06 |
| $SO_3$ | 3.00 | 0.48 | 0.18 |
| $Na_2O$ | 0.14 | 2.63 | 0.29 |
| $K_2O$ | 0.73 | 0.69 | 2.19 |
| S+A+F | - | 88.86 | 81.85 |
| Loss on ignition | 3.92 | 3.88 | 10.00 |
| Insoluble residue | 0.50 | 75.98 | 37.32 |
| Free CaO | 1.74 | - | - |

Table 2 The physical and mechanical properties of PC, diatomite and zeolite

| Materials | Compressive strength, MPa | | Setting time, minute | | Blaine, $cm^2/g$ | Specific gravity |
|---|---|---|---|---|---|---|
| | 7 days | 28 days | Initial | Final | | |
| PC | 29.6 | 52.8 | 118 | - | 4249 | 3.17 |
| Diatomite | - | - | - | - | 13640 | 2.28 |
| Zeolite | - | - | - | - | 5740 | 2.18 |

Table 3 The physical characteristic of the aggregates

| Test | | Result | | |
|---|---|---|---|---|
| Unit weight, $g/cm^3$ | Loose Unit Weight | 1.48 | | |
| | Dense Unit Weight | 1.66 | | |
| Specific gravity and Water absorption | | Aggregate grading | | |
| | | 0-5, mm | 5-19, mm | 19-30, mm |
| | Dry weight | 2.63 | 2.62 | 2.66 |
| | Saturated and surface -dry weight | 2.64 | 2.65 | 2.69 |
| | Water absorption, % | 0.61 | 1.16 | 1 |
| Moisture content, % | | 1.25 | 1.32 | 1.41 |
| Determination of organic impurities | | The color of the liquid is light yellow color than colorless (Organic matter is harmless). | | |

relevant features between input and outputs.

Adaptive network-based fuzzy inference systems (ANFIS), and artificial neural network (ANN) are the two of the most essential expert systems approaches. Both approaches are able to extract features from trained data. Henceforth, extracted features can be used during the analysis and prediction of a test data, given that both the test and train data have common characteristics and features. In terms of prediction of test data; such as mechanical behavior and physical properties of concrete and cement mortars, ANN and ANFIS are the two of the most common alternative methods that introduce efficient estimation performance (Beycioğlu *et al.* 2015, Mansouri and Kisi 2015, Kocak *et al.* 2015, Sakthivel *et al.* 2016, Subasi 2009, Topcu and Saridemir 2008, Wang *et al.* 2015, Yaprak *et al.* 2013). ANN and ANFIS approaches are based on trial and error method to find the network parameters such as number of hidden layers and neurons. Therefore, they require intense amount of computational energy. (Behnood *et al.* 2015, Behnood *et al.* 2017, Velay-Lizancos *et al.* 2017).

In this study, we introduce ANN and ANFIS models to evaluate the effect of zeolite and diatomite when used as supplementary cementitious materials on compressive strength of concrete. Such evaluation model aims to increase the efficiency in terms of labor, time and cost. Seven different binder combinations are used in this study. These seven combinations are consist of PC, 10-20% diatomite, 10-20% zeolite, 5+5-10+10% diatomite and zeolite. For the sake of the goal, 7 different cements are substituted for Portland cement. In order to define a model, we have collected 63 samples from the results of 28, 56 and 90 days compressive strength experiments of concrete, which comprises the mentioned seven cements. Having acquired the laboratory experiments, the empirical observations from laboratory experiments are utilized in training of ANN and ANFIS systems. Particularly, we defined the input parameters of ANN and ANFIS models as; age of samples (days), amount of Portland cement, zeolite, diatomite, aggregate, water and hyper plasticizer. On the other hand, output parameter of the model is defined by the compressive strength of concrete. The obtained results from compressive strength of concrete were compared with ANN and ANFIS model predictions.

## 2. Experimental study

### 2.1 Materials

In this study, CEM I 42.5 R (PC) type of cement is used and it is provided from Bolu Cement Plant. The chemical composition of the provided PC are presented in Table 1. The physical and mechanical characteristic of PC are given in Table 2. Furthermore, the diatomite is obtained from Kutahya region and zeolite from Balikesir-Bigadic region. The diatomite is supplied by ASU Chemistry and Mining Firm and zeolite is provided by a Zeolite Firm in Turkey. The chemical compositions of diatomite and zeolite are presented in Table 1, and physical and mechanical properties of diatomite and zeolite are given in Table 2. We also used crashed sand and crushed stone from Asar River aggregates in Duzce region.

The physical characteristic of the aggregates are presented in Table 3. For the purpose of the study, AYDOS Construction Chemicals Factory have produced the type of fluid 70. In terms of concrete admixtures, new generation hyper plasticizer with solid matter content of 34.32%, intensity of 1.184 (20℃), pH value of 7.26 (20℃) have been applied. For our mixing water needs, we used well water from Doganli village in Duzce.

### 2.2 Methods

During experiment, seven different binder combinations are substituted from Portland cement. The substituted

Table 4 Concrete's mixture proportion 1 $m^3$ for each concrete group

| Materials | | Specific gravity | *R*, kg | 10D, kg | 20D, kg | 10Z, kg | 20Z, kg | 5D5Z, kg | 10D10Z, kg |
|---|---|---|---|---|---|---|---|---|---|
| Aggregate | 0-5 | 2.66 | 822 | 831 | 822 | 843 | 855 | 849 | 855 |
| | 5-19 | 2.69 | 586 | 593 | 586 | 602 | 611 | 606 | 611 |
| | 19-30 | 2.70 | 428 | 433 | 428 | 439 | 446 | 442 | 445 |
| Total | | | 1836 | 1857 | 1836 | 1884 | 1912 | 1897 | 1911 |
| PC | | 3.17 | 400 | 360 | 320 | 360 | 320 | 360 | 320 |
| Diatomite | | 2.28 | - | 40 | 80 | - | - | 20 | 40 |
| Zeolite | | 2.18 | - | - | - | 40 | 80 | 20 | 40 |
| Hyper plasticizer | | 1.184 | 4.800 | 4.320 | 4.800 | 4.320 | 4.800 | 4.320 | 3.840 |
| Water | | 1 | 139.7 | 139.7 | 123.3 | 139.7 | 123.2 | 139.7 | 124.2 |

cements and their mixture proportions are explained in Section 1. We behave in accordance to standards of TS 802 (TS 802 2009) during the development of concrete mixture, and materials ratio. Based on the type and SCM rate, we produced seven types of concrete as the cement substitute. According to the additive rate and the utilized SCM, we encode the seven concretes as R, 10D, 20D, 10Z, 20Z 5D5Z and 10D10Z. Based on TS EN 12350-2, consistency of fresh concrete is defined for each mixing group individually (TS EN 12350-2 2010). We present the rate of material amounts on each sample inside concrete mixture of 1$m^3$ and their fresh concrete characteristics in Table 4.

15×15×15 cm cubes (three units cube samples have been made for each concrete group) were produced from each batch. Each specimen was demolded the next day after casting and subsequently cured by submerging the specimens in water with temperature controlled at 23±2℃. The compressive strength of the specimens was obtained by testing the specimens at 28, 56 and 90 days in accordance to TS EN 12390-6 (TS EN 12390-6 2010).

## 3. Artificial neural network

ANN is one of the most prominent computational method that simulate structure and functionalities of biological neurons. Fundamental building blocks of ANN are artificial neurons, where each neuron is interconnected to many other neurons of ANN. The ANN method has three simple sets of rules. These rules are stated as: multiplication, summation and activation. At the first phase of artificial neurons, the inputs are weighted by initial seeds, so that each input value is multiplied with individual weight. In the center-piece, there exists a summation function that sums all weighted inputs and bias. Finally, at the exit phase of artificial neuron, the sum of previously weighted inputs and bias is transmitted through activation function as the transfer function (Fig. 1) (Suzuki 2011).

The output of a neuron is transmitted to another neuron as input. Such yield is computed by multiplication of the outputs of the connected neurons via synaptic strength of the connection. As introduced in Eq. (1) below, weighted sums of the input components are computed by weights of the neighbor neurons. Furthermore, bias should be

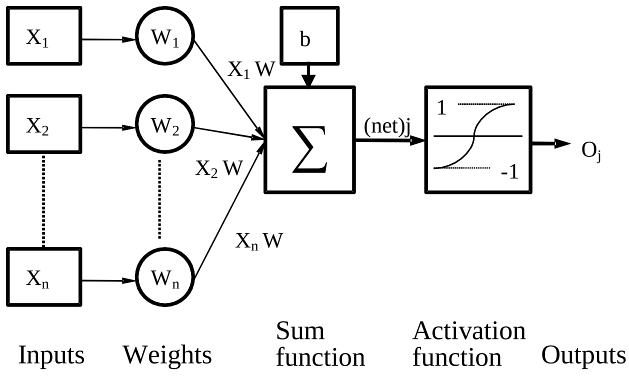


Fig. 1 The artificial neuron model

considered during the computation.

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

where: $(net)_j$, is the weighted sum of the $j^{th}$ neuron comprising bias; $w_{ij}$ is the weight between the $j^{th}$ neuron in the preceding layer; $o_i$ is the output of the $i^{th}$ neuron in the antecedent layer; $b$ is a fixed value as an internal summation of the function (Topcu *et al.* 2008).

Let assume that the inputs of a neural network are received from the preceding layer via $n$ distinguished neurons. During execution of neural network, Activation function processes the net input, which is provided from sum function and computes the neuron output. In most cases, ($f$ $(net)_j$) sigmoid activation function is used as the activation function for multilayer feed forward models. As shown in Eq. (2), the output of the $j^{th}$ neuron is computed with a sigmoid activation function (Topcu *et al.* 2009)

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

where: $o_j$ is the output of the $j^{th}$ neuron; $e$ is natural logarithm; $\alpha$ is the constant that describes the slope of the semi-linear region.

The sigmoid activates all but input layer in nonlinear form. The yield of the sigmoid function is represented by either 0 or 1. When necessary, the output range of the sigmoid function can be transformed into (−1, 1) range as well.

The sigmoid processor represents a continuous function during non-linear descriptions, since derivatives of sigmoid can be fixed easily by the parameters of $(net)_j$ (Topcu *et al.* 2009).

## 4. Adaptive network-based fuzzy inference systems

Adaptive network-based fuzzy inference system (*ANFIS)* is a hybrid system which comprises both neuronal network and fuzzy inference systems. Obviously, fuzzy inference in this hybrid system is used to handle imprecision and uncertainty. Fuzzy Logic concept allows membership degrees to the variables. Based on the if-then rules of the fuzzy inference system, each input's fuzzy sets

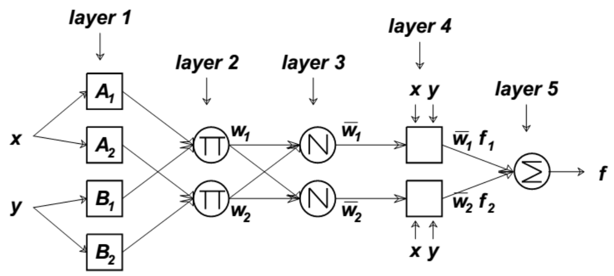


Fig. 2 Equivalent ANFIS scheme

are evaluated. As a consequence of this operation, fuzzy system can yield optimum outputs, which is close to the response outputs. The optimum results of the system bound up with the experience of the expert system. On the other hand, the neuronal network handles adaptability. Neural networks are adaptive networks which are composed of highly interconnected simple elements, adaptive nodes. They imitate human brain by setting up the right network connections. In general, neural networks are adjusted or trained so that a particular input causes particular response. Takagi, Sugeno, and Kang introduced the model, which produces fuzzy rules from an input-output data set. A typical fuzzy rule has the following format;

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

where, $A$ and $B$ are fuzzy sets in the antecedent; and $z=f(x,y)$ is a crisp function. In general, $f(x,y)$ is a polynomial grounding on the input variables; $x$ and $y$. When $f(x,y)$ is a first-order polynomial, the model becomes a first-order Sugeno fuzzy model. On the other hand, if $f$ is a constant, it is assumed as zero-order Sugeno fuzzy model. In order to make precise definitions, let consider a first-order Sugeno fuzzy inference system which contains two fuzzy *If-then* rules as follows:

*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 terms of ANFIS inference, output of each rule is a linear combination of the input variables taking part by a fixed term such as $p_1$, $q_1$ and $r_i$. The final output of the inference system is established by the weighted average ( $\overline{w}_i$ ) of each rule's output (Aali *et al.* 2009, Jang 1996, Atmaca *et al.* 2001).

The equivalent ANFIS scheme is shown in Fig. 2, where node of a coequal layer performs same task. In general, ANFIS structural model is consist of five layers. In order to ensure precise explanation, let assume that $O_i^j$ denotes the output of the $i^{th}$ node in $j^{th}$ layer is preferred.

The Layer 1 is defined as Fuzzification Layer. In this layer, every node $i$ in the layer is an adaptive node with following 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 an input to the $i$ th node, and $A_i$ or $B_{i-2}$ is a linguistic label such as *tall*, *short*. On the other hand, $O_i^j$ 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 $a_i$, $b_i$, $c_i$ are the parameter coefficients. In view of parameters changes, the bell-shaped function will vary correspondingly; henceforth exhibiting various forms of membership functions on linguistic label, $A_i$. Parameters of this layer are referred as premise parameters. The outputs of the layer are assumed as the membership values of the premise part.

The Layer 2 of ANFIS is defined as Rule inference layer. Each rule is assigned a firing strength which measures the degree to which the rule matches the inputs. In this layer, each node computes the firing strength of a rule by multiplication as follows

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

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

The Layer 3 of ANFIS is defined as Normalization layer. A member of this layer, Node $i$, computes the ratio between $i^{th}$ rule's firing strength and all firing strengths. Formally

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

The outputs of third layer are named as normalized firing strengths.

The Layer 4 of ANFIS is defined as Consequent layer. A member of this layer, Node $i$, computes the contribution of $i$-th rule toward the overall output. Mathematically

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

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

Finally, Layer 5 is defined as the Output layer. This layer's single fixed node, labeled as $\sum$, computes the final output as the summation of all incoming signals.

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

In summary, fundamental learning strategy of ANFIS is based on backpropagation gradient descent, which calculates error signals in a bottom up approach recursively. Precisely, ANFIS starts the execution from output layer through to the nodes of input layer. In this strategy, error signals are determined by the derivative of the squared error with respect to each node's output. In fact, such learning strategy is similar to the backpropagation learning.

## 5. Experimental design and model parameters

In terms of training and testing of the ANN and ANFIS, we used seven input parameters: age of samples (days),

Table 5 Utilized input and output parameters and their quantities during ANN model

| | | Utilized training and testing data of the model | |
|---|---|---|---|
| | | Minimum | Maximum |
| Input variable | Age of samples, days | 28 | 90 |
| | PC, kg | 320 | 400 |
| | Zeolite, kg | 0 | 80 |
| | Diatomite, kg | 0 | 80 |
| | Aggregate, kg | 1836 | 1912 |
| | Water, kg | 123.2 | 139.7 |
| | Hyper plasticizer, kg | 3.840 | 4.800 |
| Output variable | Compressive strength, MPa | 42.8 | 67.9 |

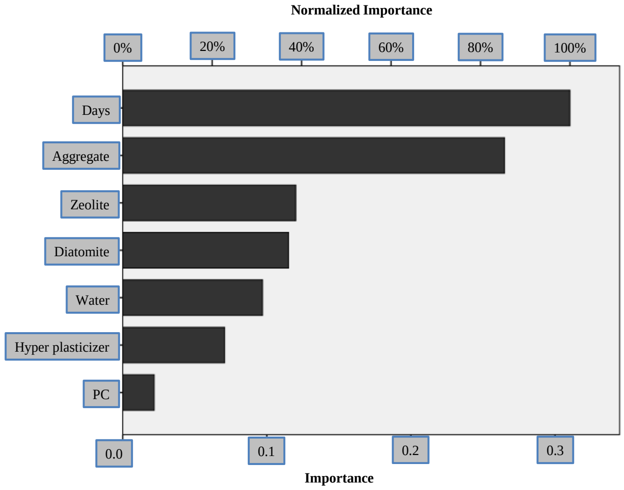


Fig. 3 Degree importance of the input variables

amount of PC, zeolite, diatomite, aggregate, water and hyper plasticizer. The response parameter is compressive strength and the ranges of the input parameters are presented in Table 5. The sensitivity levels of the input variables are computed by using SPSS 22.0 software package and importance level of the aforementioned variables are presented in Fig. 3. The significance levels of the input parameters are as follows:

- days : 0.31
- aggregate : 0.265
- zeolite : 0.120
- diatomite : 0.115
- water : 0.097
- hyper plasticizer : 0.071
- PC : 0.022

Table 6 Parameters of the model in quantitative form

| Parameters | ANN model values |
|---|---|
| Number of input layer neurons | 7 |
| Number of hidden layer | 2 |
| Number of first hidden layer neurons | 10 |
| Number of second hidden layer neurons | 5 |
| Number of output layer neuron | 1 |
| Error after learning | $1\times10^{-7}$ |
| Learning cycle | 6 |

In the ANN and ANFIS models, we utilized 63 data for training and 21 data for testing purposes. As shown in Table 7, we considered 21 different criteria for the experiments. From each criterion, we collected 3 observations to achieve 63 training data. In order to obtain testing data, we compute the average of 3 observations for each criterion.

Our ANN architecture consist of six components. These components are feed-forward back propagation, two hidden layers, training function (Levenberg-Marquardt), adaptation learning function (learngdm), transfer function (tansig) and performance function (MSE-mean squared error). These components are visually presented in Fig. 4. Quantitatively, exploited neurons in the first and second layers of ANN model are 10 and 5 respectively. Furthermore, both momentum rate and learning rate values were also determined and the model was trained through iterations. The quantitative parameters of the multilayer feed-forward neural network model are presented in Table 6.

There are seven input parameters incorporated in ANFIS model. These inputs are; the days, PC, zeolite, diatomite, aggregate, water and hyper plasticizer and an output compressive strength of the concrete and units of these input parameters are demonstrated in Fig. 5. We have done intense computational experimentations with various neural network epochs. Results of the different learning algorithms with different epochs, best correlations were found through hybrid learning algorithm and 6 epochs. Furthermore, two "gbellmf" membership functions for each input variables were selected for the days, PC, zeolite, diatomite, aggregate, water and hyper plasticizer. Compressive strength has been nominated as the output variable of the expert system implementations. The membership function for each input parameter is presented in Fig. 6.

## 6. Results and discussion

In this study, we estimate the value of compressive

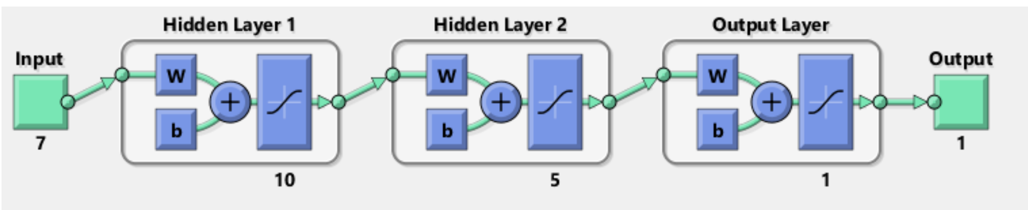


Fig. 4 The architecture used in the neural network model for compressive strength

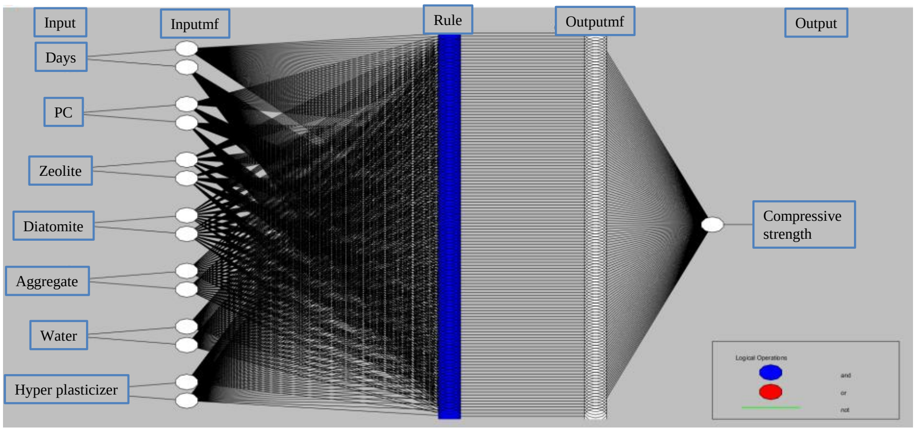


Fig. 5 General structure of the model

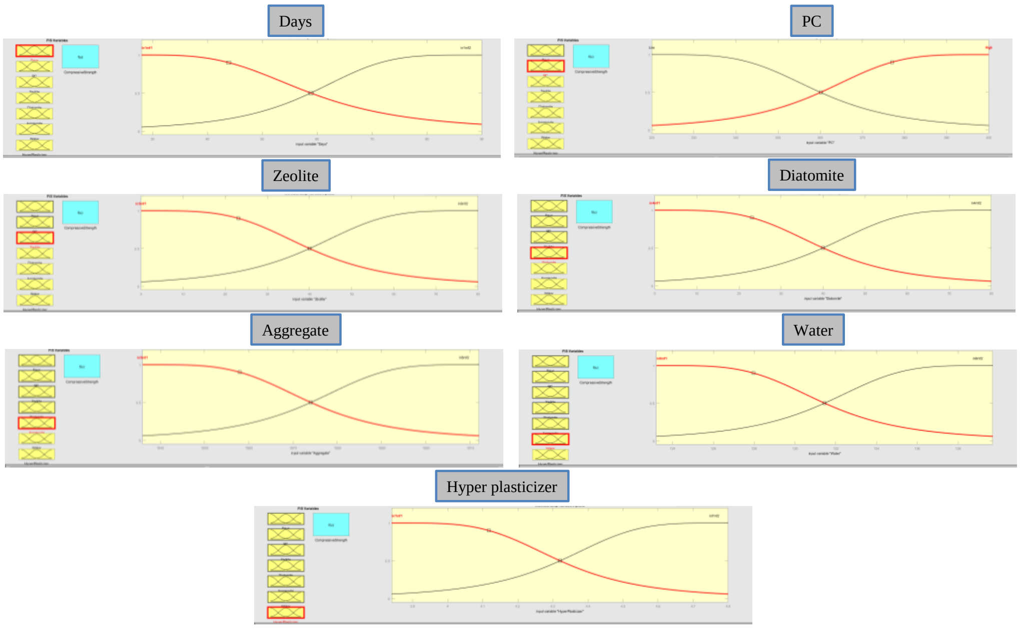


Fig. 6 Membership functions of input variables

strength of concrete experiments by using artificial intelligence models, which are ANN and ANFIS. In order to evaluate the estimation and efficiency performance of the models, we made use of three common criteria that compares the predictions of expert systems and laboratory experiments. For evaluating the robustness of the network models, several parameters are used as indicators. These parameters are absolute fraction of variance ($R^2$), mean absolute percentage error (MAPE), and root-mean squared (RMS) error. The formula for $R^2$, MAPE, and RMS are presented in Eq. (8) to Eq. (10) (Ozcan *et al.* 2009).

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

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

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

In Eqs. (8), (9) and (10) ***t*** is defined as the target value, and ***o*** is defined as the network output value. On the other hand, we let ***N*** as the number of patterns to be analyzed.

We have collected 63 observation data from concrete experiments. We utilized the 63 of them during the training ANN and ANFIS models. In order to obtain testing data, we compute the average of 3 observations for each criterion. The 21 data is reserved for testing purposes, which maintain the average properties of train data.

In order to ensure precise explanation, we introduced sample number and yield of ANN estimation model in Fig. 7.

Fig. 8 presents the sample numbers, and comparison of the experimental results versus estimations of ANN and ANFIS models.

The results of compressive strength obtained from experiment, ANN & ANFIS analysis along with the detail

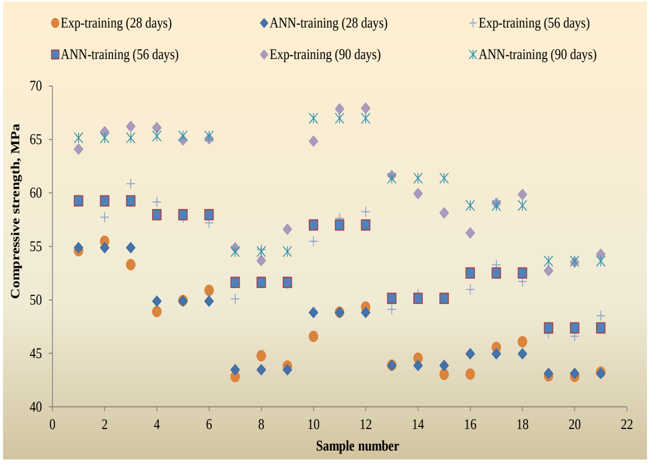


Fig. 7 Comparison of compressive strength experimental and training results of ANN model with sample number

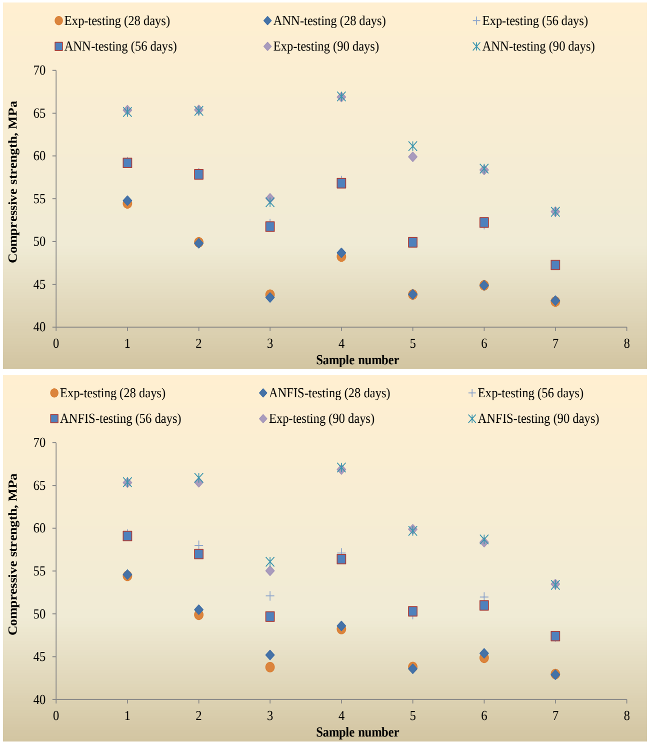


Fig. 8 Comparison of compressive strength experimental and testing results of ANN and ANFIS models with sample number

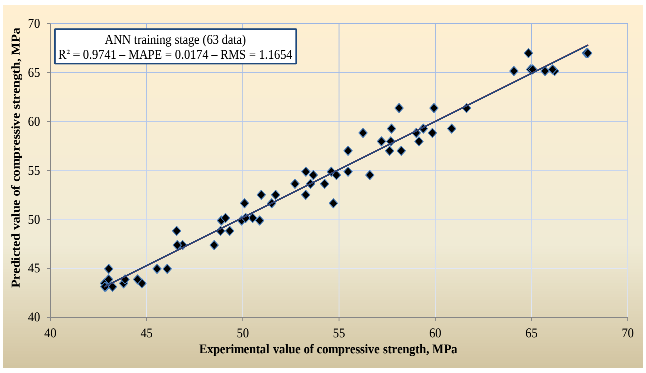


Fig. 9 Comparison of compressive strength experimental results with training results of ANN model

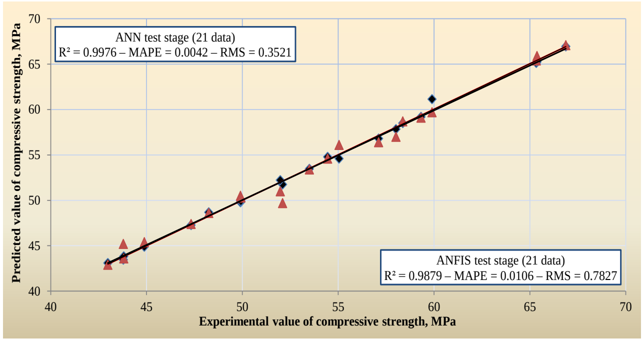


Fig. 10 Comparison of compressive strength experimental results with testing results of ANN (♦) and ANFIS (▲) models

Table 7 Comparison of compressive strength experimental results with testing results obtained from ANN and ANFIS

| Data used in the model construction | | | | | | | Compressive strength, MPa | | |
|---|---|---|---|---|---|---|---|---|---|
| As, days | PC, kg | Zeolite, kg | Diatomite, kg | Aggregate, kg | Water, kg | HP, kg | Exp. | ANN | ANFIS |
| 28 | 400 | 0 | 0 | 1836 | 139.7 | 4.80 | 54.4 | 54.8 | 54.6 |
| 28 | 360 | 0 | 40 | 1857 | 139.10 | 4.32 | 49.9 | 49.8 | 50.5 |
| 28 | 320 | 0 | 80 | 1836 | 123.3 | 4.80 | 43.8 | 43.5 | 45.2 |
| 28 | 360 | 40 | 0 | 1884 | 139.7 | 4.32 | 48.2 | 48.7 | 48.6 |
| 28 | 320 | 80 | 0 | 1912 | 123.2 | 4.80 | 43.8 | 43.8 | 43.6 |
| 28 | 360 | 20 | 20 | 1897 | 139.7 | 4.32 | 44.9 | 44.9 | 45.4 |
| 28 | 320 | 40 | 40 | 1911 | 124.2 | 3.84 | 43.0 | 43.1 | 42.9 |
| 56 | 400 | 0 | 0 | 1836 | 139.7 | 4.80 | 59.3 | 59.2 | 59.1 |
| 56 | 360 | 0 | 40 | 1857 | 139.10 | 4.32 | 58.0 | 57.8 | 57.0 |
| 56 | 320 | 0 | 80 | 1836 | 123.3 | 4.80 | 52.1 | 51.7 | 49.7 |
| 56 | 360 | 40 | 0 | 1884 | 139.7 | 4.32 | 57.1 | 56.8 | 56.4 |
| 56 | 320 | 80 | 0 | 1912 | 123.2 | 4.80 | 49.9 | 49.9 | 50.3 |
| 56 | 360 | 20 | 20 | 1897 | 139.7 | 4.32 | 52.0 | 52.2 | 51.0 |
| 56 | 320 | 40 | 40 | 1911 | 124.2 | 3.84 | 47.3 | 47.3 | 47.4 |
| 90 | 400 | 0 | 0 | 1836 | 139.7 | 4.80 | 65.3 | 65.1 | 65.4 |
| 90 | 360 | 0 | 40 | 1857 | 139.10 | 4.32 | 65.4 | 65.3 | 65.9 |
| 90 | 320 | 0 | 80 | 1836 | 123.3 | 4.80 | 55.0 | 54.6 | 56.1 |
| 90 | 360 | 40 | 0 | 1884 | 139.7 | 4.32 | 66.9 | 66.9 | 67.1 |
| 90 | 320 | 80 | 0 | 1912 | 123.2 | 4.80 | 59.9 | 61.1 | 59.7 |
| 90 | 360 | 20 | 20 | 1897 | 139.7 | 4.32 | 58.4 | 58.5 | 58.7 |
| 90 | 320 | 40 | 40 | 1911 | 124.2 | 3.84 | 53.5 | 53.5 | 53.4 |

of the input parameter values are presented in Table 7.

The quantitative data are collected through experiment. These data are later used for training and testing purposes of ANN and ANFIS models. In Figs. 9 and 10, we denote the 28, 56 and 90 days' compressive strength estimations of ANN and ANFIS models and subsequently, the comparisons of the collected data from laboratory experiments.

In Figs. 9 and 10, we present linear least square fit line, and the $R^2$ values of the experiments and predicted values of compressive strength. Results in Figs. 9 and 10 denotes ANN and ANFIS models successfully predicts compressive strength of concrete containing zeolite and diatomite. In both figures, it is possible to draw a regression line between experimental compressive strength and predictions, whose

Table 8 The compressive strength statistical values of proposed ANN and ANFIS models

| Statistical parameters | ANN | | ANFIS |
|---|---|---|---|
| | Training set | Testing set | Testing set |
| $R^2$ | 0.9741 | 0.9976 | 0.9879 |
| MAPE | 0.0174 | 0.0042 | 0.0106 |
| RMS | 1.1654 | 0.3521 | 0.7827 |

Table 9 Statistical comparison of experimental values with ANFIS and ANN model test values

| | | Experimental | ANFIS | ANN |
|---|---|---|---|---|
| Experimental | Pearson Correlation | 1 | 0.994** | 0.999** |
| | Sig. (2-tailed) | - | 0.000 | 0.000 |
| | Covariance | 53.167 | 52.532 | 53.312 |
| | Test samples (N) | 21 | 21 | 21 |

** Correlation is significant at the 0.01 level (2-tailed).

distance to all points is small enough. In the figures, RMS, $R^2$ and MAPE results supports such claim with quantitative results. As a consequence, it is possible to claim that ANN and ANFIS models are capable to make good predictions that can generalize a computational algorithm between input and output variables.

In terms of RMS, $R^2$ and MAPE, the statistical results of ANN and ANFIS models for both training and testing sets were presented in Table 8.

As can be seen in Table 8, statistical values of $R^2$, MAPE and RMS from training in the ANN model were found as 0.9741, 0.0174 and 1.1654. In the same manner, these testing values of aforementioned statistical parameters are 0.9976, 0.0042 and 0.3521 respectively. The statistical values of $R^2$, MAPE and RMS from testing in the ANFIS model were found as 0.9879, 0.0106 and 0.7827, respectively. These results satisfy the goals of the study. In addition to the above statistical evaluations, we have observed statistical relationship and correlation between experimental data and the expert system model when compressive strength values are considered in (Table 9).

## 7. Conclusions

Due to plentiful zeolite and diatomite resources in Turkey, we have motivated on compressive strength analysis of concrete containing zeolite and diatomite. In general, compressive strength analysis of concrete is implemented in the laboratory and contribution of the zeolite and diatomite on the compressive strength must be analyzed. During the laboratory experiments of compressive strength, three basic resources are needed. These are financial costs, labor, and time. In order to utilize the resources in an efficient form, computerized techniques are also used in literature. Particularly, computer based techniques are used to estimate chemical reactions of concrete such as compressive strength.

In terms data analysis, ANN and ANFIS are two of the most common expert system models that can learn from the training data. During the learning phase, both models establish neural rules between input and response values. Those neural rules are then can be used to estimate test data behaviors.

During this study, we utilized ANN and ANFIS models and estimated the 28, 56 and 90 days compressive strength of concrete, which contain either zeolite, diatomite, both zeolite and diatomite. In order to develop the expert system models, we collected 63 data from laboratory experiments. We reserved the 63 of data for training and 21 data (the average of the 3 experimental data for each concrete group) are employed for testing purposes. We attach importance to ensure that test data fairly represent the average of training data. While developing ANN and ANFIS models, we tested different learning algorithms with different epochs to define a model which introduces potentially best estimation ability. After finding the best ANN and ANFIS models, and consequently most accurate executions of ANN and ANFIS, we did comprehensive comparisons to achieve our goals that have mentioned. In order to compare the ANN, ANFIS and experimental results, $R^2$, MAPE and RMS statistics were utilized as the essential evaluation criteria. When laboratory experiments are compared to expert system models, we observed that both ANN and ANFIS models yield significant result and they can be used to reduce labor, time and financial costs. Particularly, the estimations and the experimental values in the training stage $R^2$, MAPE and RMS were found as 0.9741, 0.0174 and 1.1654 for ANN model, respectively. When the test stage is considered, $R^2$, MAPE and RMS were found as 0.9976, 0.0042 and 0.3521 for ANN model and 0.9879, 0.0106 and 0.7827 for ANFIS model, respectively. The results denote that both expert system models yielded significant results. The statistical parameter values of $R^2$, MAPE and RMS that compared experimental data against ANN and ANFIS models estimations have verified our goals.

Arising from the results of this study, we have concluded that compressive strength values of concrete containing zeolite, diatomite, both zeolite and diatomite can be predicted in the ANN and ANFIS models in a quite short period of time with small error rates. The estimation results have shown that ANN and ANFIS systems are practicable methods for predicting compressive strength values of concrete containing zeolite, diatomite, both zeolite and diatomite. Furthermore, these systems can reduce losses in both elapsed time and financial costs during the preparation of the cement mortars and concretes by utilizing various additives. In the future, new studies can focus on the removing limitations including but not limited to the concrete types that may be prepared with various supplementary cementitious materials.

## Acknowledgements

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).

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