International Journal of Sustainable Built Environment (2016) 5, 355–369

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International Journal of Sustainable Built Environment

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Original Article/Research

Predicting strength of recycled aggregate concrete using Artificial Neural Network, Adaptive Neuro-Fuzzy Inference System and Multiple Linear Regression

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Received 26 August 2016; accepted 17 September 2016

Abstract

Compressive strength of concrete, recognized as one of the most significant mechanical properties of concrete, is identified as one of the most essential factors for the quality assurance of concrete. In the current study, three different data-driven models, i.e., Artificial Neural Network (ANN), Adaptive Neuro-Fuzzy Inference System (ANFIS), and Multiple Linear Regression (MLR) were used to predict the 28 days compressive strength of recycled aggregate concrete (RAC). Recycled aggregate is the current need of the hour owing to its environmental pleasant aspect of re-using the wastes due to construction. 14 different input parameters, including both dimensional and non-dimensional parameters, were used in this study for predicting the 28 days compressive strength of concrete. The present study concluded that estimation of 28 days compressive strength of recycled aggregate concrete was performed better by ANN and ANFIS in comparison to MLR. In other words, comparing the test step of all the three models, it can be concluded that the MLR model is better to be utilized for preliminary mix design of concrete, and ANN and ANFIS models are suggested to be used in the mix design optimization and in the case of higher accuracy necessities. In addition, the performance of data-driven models with and without the non-dimensional parameters is explored. It was observed that the data-driven models show better accuracy when the non-dimensional parameters were used as additional input parameters. Furthermore, the effect of each non-dimensional parameter on the performance of each data-driven model is investigated. Finally, the effect of number of input parameters on 28 days compressive strength of concrete is examined.

Keywords: ANN; ANFIS; MLR; Data-driven models; Recycled aggregate concrete

Abbreviations: ANFIS, Adaptive Neuro-Fuzzy Inference System; ANN, Artificial Neural Network; MLR, Multiple Linear Regression; NFA, natural fine aggregate; RFA, recycled fine aggregate; NCA10, natural coarse aggregates 10 mm; NCA20, natural coarse aggregates 20 mm; RCA10, recycled coarse aggregates 10 mm; RCA20, recycled coarse aggregates 20 mm; AD, admixture; MSE, mean square value; SSE, sum of squared errors.

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Peer review under responsibility of The Gulf Organisation for Research and Development.

http://dx.doi.org/10.1016/j.ijsbe.2016.09.003

1. Introduction

Scientists have always been concerned about the depleting natural resources and their scarcity has always been one of the most important issues they have been struggling with. Therefore, reducing the impact of this scarcity and protecting the environment has always been an important issue to scientists. One of the achievable keys to decrease this impact may be using construction and demolition waste (C&D) as replacement to natural resources, especially in concrete mix designs. C&D waste, specifically the concrete waste can be turned to recycled aggregates (RA) which can be used in concrete mixes. Adding the recycled aggregates to concrete mixes is termed as recycled aggregate concrete (RAC).

Scientists have investigated the effect of RA on characteristics of concrete such as tensile strength, compressive strength, etc. (Ajdukiewicz and Kliszczewicz, 2002; Tu et al., 2006; Deshpande et al., 2011; Ryu, 2002). Using RA as a replacement to natural aggregates would result in the reduction in the compressive strength of RAC since they hold attached mortar to the aggregates. In addition, the prevailing criterion for the concrete with RA is the reduction of the density of RAC because of the water absorption by the mortar on the aggregates. Furthermore, the workability of RAC is less than the concrete with conventional aggregates because of the same explained water absorption. Finally, replacing the natural aggregates by RA which would lead to the reduction of the compressive strength might be because of the weaker connections between mortar and RCA (Ajdukiewicz and Kliszczewicz, 2002; Deshpande et al., 2014). Compressive strength of concrete, recognized as one of the most significant mechanical properties of concrete, is identified as one of the most essential factors for the quality assurance of concrete. Studies have also shown that the level of the compressive strength of RAC highly depends on the strength of RA and therefore, the strength of RAC made of RA with lower strength is less than that of concrete made of RA with higher strength, and the extent of the reduction is dependent on many factors, such as the type of concrete, W/C ratios, moisture percentages, replacement ratios, etc. (Ajdukiewicz and Kliszczewicz, 2002; Tu et al., 2006; Ryu, 2002; Khademi et al., 2015a). Accordingly, this diverse behavior of RA and RAC would lead to widespread testing to reach more understandings of their performances. Nevertheless, these different testings are time consuming, expensive, and require large amounts of materials. Therefore, in order to estimate the compressive strength of concrete, data-driven models which are based on measured data can be a good replacement for this extensive testing.

Scientists have used data-driven models broadly in the field of civil engineering. Jiang et al. have found the Artificial Neural Network capable in predicting the concrete corrosion of sewers (Jiang et al., 2016). Sadowski and Nikoo (2014) have concluded that the Imperialist Competitive Algorithm is an efficient technique in estimating the corrosion current density of reinforced concrete (Sadowski and Nikoo, 2014). Khademi and Behfarnia (2016) have concluded that the Artificial Neural Network is a suitable model in predicting the compressive strength of concrete, however, Multiple Linear Regression is not capable enough in the same prediction purposes (Khademi and Behfarnia, 2016). Nikoo et al. have claimed that the Artificial Neural Network is a talented method in approximating the displacement in concrete reinforcement building (Nikoo et al., 2012). Padmini et al. have successfully used the neuro-fuzzy models in determining the ultimate bearing capacity of shallow foundations (Padmini et al., 2008). (Khademi and Jamal, 2016) have found the Artificial Neural Network proficient in estimating the 28 days compressive strength of concrete (Khademi and Jamal, 2016).

The present study proposes three different data-driven models, i.e., Artificial Neural Network (ANN), Adaptive Neuro Fuzzy Inference System (ANFIS), and Multiple Linear Regression (MLR) models to predict the 28 days compressive strength of concrete using 14 different input variables. In addition, the performance of data-driven models with and without the non-dimensional parameters is explored. Furthermore, the effect of each non-dimensional parameter on performance of all the presented data-driven models is investigated. Finally, the effect of number of input parameters on prediction of 28 days compressive strength of concrete is studied.

2. Data preparation

In the present study, a total of 257 data sets was collected from fresh experiments performed by authors (Ajdukiewicz and Kliszczewicz, 2002; Tu et al., 2006; Ryu, 2002; Deshpande et al., 2014; Hansen and Narud, 1983; Rao et al., 2011; Yong et al., 2009; Akbari et al., 2011; Katz, 2003; Padmini et al., 2002; Dapena et al., 2010; Fathifazl et al., 2009; Agarwal et al., 2011; Yaprak et al., 2011; Schoppe, 2011; Zega and Di Maio, 2009; Duangthidar et al., 2010; Poon et al., 2004; Adnan et al., 2011; Domingo-Cabo et al., 2009; Kou, 2006; Pereira et al., 2012; Lu et al., 2004; Gonçalves et al., 2004; Corinaldesi, 2010; Li, 2011). The parameters were divided into three categorizations of mandatory elements, non-dimensional elements, and output elements described in the following:

(A) Mandatory Elements (Raw Data): The weight per cubic meter is considered as raw data based on standard mix design procedures followed worldwide (Deshpande et al., 2014; Sadrmomtazi et al., 2013). In this study, the mandatory parameters are cement (C), natural fine aggregate (NFA), recycled fine aggregate (RFA), natural coarse aggregates 10 mm (NCA10), natural coarse aggregates 20 mm (NCA20), recycled coarse aggregates 10 mm (RCA10), recycled coarse aggregates 20 mm (RCA200), admixture (AD), and water (W).

Table 1
Characteristics of input and output elements.

Parameter	Unit	Minimum	Maximum
Cement (C)	(kg/m^3)	235	645
Natural fine aggregate (NFA)	(kg/m^3)	0	1050
Recycled fine aggregate (RFA)	(kg/m^3)	0	1050
Natural coarse aggregate 20 mm (NCA20)	(kg/m^3)	0	1508.64
Natural coarse aggregate 10 mm (NCA10)	(kg/m^3)	0	553
Recycled coarse aggregate 20 mm (RCA20)	(kg/m^3)	0	1508.64
Recycled coarse aggregate 10 mm (RCA10)	(kg/m^3)	0	840
Water (W)	(kg/m^3)	120	358
Admixture (AD)	(kg/m^3)	0	10.4
Aggregate to cement ratio (A/C)	–	2.279	9.327
Water to cement ratio (W/C)	–	0.299	1.028
Sand to aggregate ratio (S/A)	–	0.149	1.566
Replacement ratio (RR) (%)	–	0	100
Water to total materials (W/T)	–	11.287	11.553
28 days compressive strength of concrete	(N/mm^2)	10.319	100.5

Table 2
Number of patterns in each specific range of 28 days compressive strength of concrete.

Number	Compressive Strength of concrete Range (kg/m^3)	Number of Patterns
1	0–20	15
2	20–40	110
3	40–60	98
4	60–80	28
5	80–100	5
6	100–150	1
Total		257

(B) Non-dimensional Elements: Any ratio of the mandatory parameters is considered as the non-dimensional elements. In this study, the non-dimensional parameters are water-cement ratio (W/C), sand-aggregate ratio (S/A), water to total materials ratio (W/T), replacement ratio of recycled aggregate to natural aggregate by volume (RR), and aggregate to cement ratio (A/C).

(C) Output Element (Dependent Parameter): In this study, the 28 days compressive strength of recycled aggregate concrete is considered as the output parameter.

It is worth mentioning that in this study both the categorization of (A) and (B) are used as input variables and the categorization (C) is used as output variable in the data-driven modeling purposes. The range of these parameters (Deshpande et al., 2014) is presented in Table 1.

In addition, the number of 28 days compressive strength patterns in each specific interval is shown in Table 2.

3. Estimation techniques

The prediction models, known as estimators, use the measured data as input variables in their data-driven modeling. In all the prediction models, there is a step involved called "training step" which assists the model to learn from a collection of training patterns (Khademi and Behfarnia, 2016). In the current study, three different data-driven models, i.e. Multiple Linear Regression (MLR), Artificial Neural Network (ANN), and Adaptive Neuro-Fuzzy Inference System (ANFIS) are used as the prediction models, each explained briefly in the following.

3.1. Multiple Linear Regression model (MLR)

Regression models generally estimate the level of correlation between the input and output variables and determine their relationship form. Linear regressions are mostly fitted by the least squares approach, however, they might be fitted using other methods, like by minimizing the "lack of fit" in some other norms or by minimizing the penalized version of the least squares loss function as in ridge regression. Basically, the linear regression is divided into two categorizations of simple and Multiple Linear Regression. If the aim is to estimate the linear correlation between one predictor and one criterion variable, the model is assumed as the simple linear regression (SLR), however, if the goal is to predict the linear correlation between two or more predictors and still one criterion variable, the model is called Multiple Linear Regression (MLR). It is worth mentioning that the MLR is the most common form of linear regression analysis and every value of the independent variable is associated with a value of dependent variable.

Normally, MLR estimates the level of correlation between one response variable (dependent variable) from two or more predictors (Independent variable). It should be emphasized that the MLR explores a correlation in terms of a straight line that best predicts all the individual data points containing both target and output variables (Khademi and Behfarnia, 2016). The general form of a MLR model is as shown in Eq. (1) Chou and Tsai, 2012; Bingöl et al., 2013:

$$\hat{Y} = a_0 + \sum_{j=1}^{m} a_j X_j \tag{1}$$

where $\hat{Y}$ is the model's output, X_j's are the independent input variables to the model, and $a_0, a_1, a_2, \ldots, a_m$ are partial regression coefficients.

3.2. Artificial Neural Network (ANN)

Artificial Neural Network (ANN) is a data processing system inspired by the configuration of the human brain. ANN is basically made of artificial neurons which are identified as the highly interconnected processing constituents acting altogether to achieve a specific problem (Khademi and Jamal, 2016). Generally, ANN is used in complex states where the customary computational techniques are not efficient enough to resolve them.

It is worth mentioning that in the ANN model, the relationship between the predictors and output elements are produced by the data themselves, and accordingly, the ANN is talented to learn from examples widely. In addition, ANN is efficient in incomplete tasks and estimated outcomes. Therefore, these two considerable characteristics distinguish ANN from many other data-driven models and results in usability of high majority of researchers.

The general structure of ANN is shown in Fig. 1. The network contains different layers of neurons. In order to predict any measurable functional relation between predictors and output parameters to any desirable accuracy, one hidden layer comprising a number of nodes is recommended and this recommendation is used in the current study.

The strength of connections is determined using weighted connections. These weights are trained in such as way that assists the ANN model to make the output variables as close as possible to target values. ANN is comprised of three steps of training, validation, and test. The most important acting of the training step is to minimize the error function, mean square value (MSE), as n example, presented in Eq. (2) Chen, 2010; Jang, 1993:

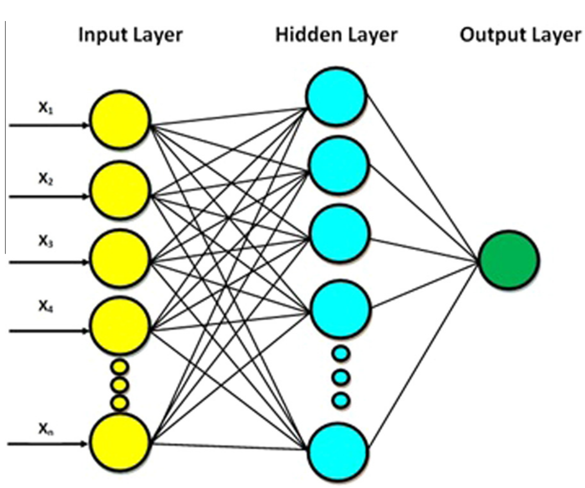

Figure 1. Structure of ANN model.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(t_i - a_i)^2 \tag{2}$$

where "N" is the number of data, t_i are the output values, and a_i are the target value values.

The validation step which is sometimes called the check step in other data-driven modeling, ANN model, as an example, is used for the construction purposes and performs independently from the training step. Lastly, the test step is used to predict the machine algorithm accuracy.

3.3. Adaptive Neuro Fuzzy Inference System (ANFIS)

Adaptive Neuro Fuzzy Inference System (ANFIS) is identified as a universal estimator for responding to complex problems. ANFIS is a class of adaptive, multi-layer and feed-forward networks which is comprised of input–output variables and a fuzzy rule base of the Takagi–Sugeno type. The fuzzy reasoning mechanism of ANFIS model with two fuzzy if-then rules for a first-order Sugeno fuzzy model is expressed as (Mosavi and Nik, 2015):

Rule 1: 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 $f_2 = p_2\ x + q_2\ y + r_2$.

The framework of ANFIS contains five layers, which act differently from each other; however, the nodes of the same layer perform similar to each other. The structure of ANFIS is shown in Fig. 2.

As it is shown in Fig. 2, the structure of ANFIS is comprised of five different layers which are explained briefly in the following:

Layer 1: This layer takes the responsibility for fuzzification of input feature values in the range of 0 to 1. The required values such as membership functions for each ith node are defined in this layer, shown in Eq. (3):

$$O_i^1 = \mu_{A_i}(x) \tag{3}$$

where x is the input to node i and A_i is the linguistic label associated with this node function.

Layer 2: Each rule is a node in the ANFIS by using soft-min or product to find out the rule matching factor w_i. The incoming signals are multiplied in this layer and sent the product out, shown in Eq. (4).

$$w_i = \mu_{A_i}(y) \times \mu_{B_i}(y), i = 1, 2 \tag{4}$$

Layer 3: The membership values are getting normalized in this layer. The formulation of normalized firing strength for node *ith* in this layer is shown in Eq. (5).

$$w_i = \frac{w_i}{(w_1 + w_2)}, i = 1, 2 \tag{5}$$

Layer 4: This layer is able to establish the relationship between the input and output values, shown in Eq. (6).

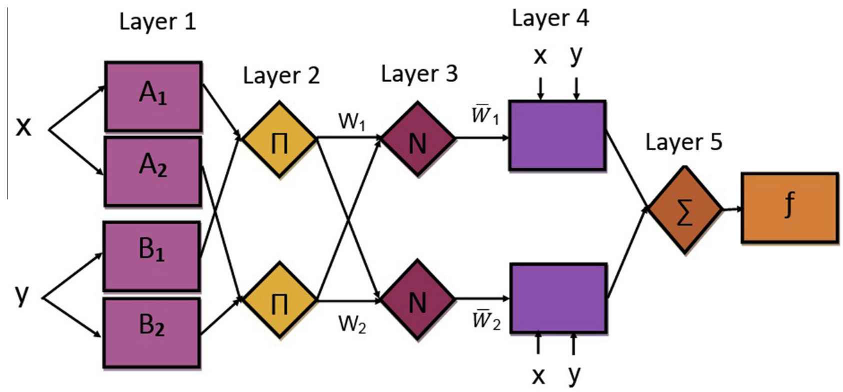

Figure 2. Structure of ANFIS model with two input variables.

$$O_i^4 = w_i(p_i x + q_i y + r_i) \tag{6}$$

where $\hat{w}_i$ is the output resulted from layer 3, and $\{p_i, q_i, r_i\}$ is the parameter set.

Layer 5: This layer which is also called the defuzzification layer consists of one single node which generates the summation of all incoming signals from previous node and results in a single value. In this layer, each rule output is added to the output layer. Overall output can be calculated using Eq. (7).

$$\mathrm{O}_\mathrm{i}^5 = \sum\nolimits_\mathrm{i} \overline{\mathrm{w}}_\mathrm{i} \mathrm{f}_\mathrm{i} = \frac{\sum_\mathrm{i} \mathrm{w}_\mathrm{i} \mathrm{f}_\mathrm{i}}{\sum_\mathrm{i} \mathrm{w}_\mathrm{i}} \tag{7}$$

4. Methodology

In recent years, researchers have investigated widely on various types of civil engineering materials, specifically concrete and cement (Khademi and Jamal, 2016; Nik et al., 2010; Gandomi et al., 2016; Bahari et al., 2012a; MATLAB and Statistics Toolbox Release, 2014). The 28 days compressive strength of concrete is assumed as the standard compressive strength of concrete, and as a result, in both the engineering decisions and concrete constructions, estimating the compressive strength of concrete is a significant fact (Khademi and Jamal, 2016). In this study, 257 concrete mix designs were used to estimate the 28 days compressive strength of concrete. Three different data-driven models, i.e., Multiple Linear Regression (MLR), Artificial Neural Network (ANN), and Adaptive Neuro-Fuzzy Inference System (ANFIS) were selected as the prediction models and the estimation for the compressive strength of concrete has been obtained. The dataset was divided into two subsets of training and testing for the MLR model, however, they were divided into three subsets of training, validation, and testing for both ANN and ANFIS models. All the data driven modeling have been developed in MATLAB software (Nazari and Khalaj, 2012). First, MLR, ANN, and ANFIS models were compared with each other in case of prediction capabilities. Next, the sensitivity analysis was performed on the dataset in case of efficiency of each single input parameter on compressive strength of concrete. Finally, the sensitivity analysis was performed in case of the efficiency of the number of input parameters on compressive strength of concrete. The performance criterion for comparing the results is chosen as coefficient of determination (R^2), shown in Eq. (8) Nikoo et al., 2015a:

$$R^2 = \frac{\left[\sum_{i=1}^{n}(y_i - \overline{y})(\hat{y}_i - \overline{\hat{y}})\right]^2}{\sum_{i=1}^{n}(y_i - \overline{y})^2 \sum_{i=1}^{n}(\hat{y}_i - \overline{\hat{y}})^2} \tag{8}$$

where "y_i" is the experimental strength of "ith" specimen "$\overline{y}$" is the averaged experimental strength, "$\hat{y}_i$" is the calculated compressive strength of "i" th specimen, and "$\overline{\hat{y}}$" is the averaged calculated compressive strength.

Also, the sum of squared errors (SSE) and Mean squared error (MSE) for all the three models is calculated and compared with each other. The formula of SSE and MSE are presented in Eqs. (9) and (2), respectively:

$$SSE = \sum_{i=1}^{N}(x_i - \overline{x}_i)^2 \tag{9}$$

where n is the number of the specimens, x_i is the measured compressive strength and $\overline{x}_i$ is the predicted compressive strength.

4.1. Comparison of MLR, ANN, and ANFIS models

In order to compare the MLR, ANN, and ANFIS models, 14 different concrete mix parameters have been chosen as input variables. These input parameters are divided into two categorizations of mandatory and non-dimensional elements. Mandatory parameters include cement (C), natural fine aggregate (NFA), recycled fine aggregate (RFA), natural coarse aggregates 10 mm (NCA10), natural coarse aggregates 20 mm (NCA20), recycled coarse aggregates 10 mm (RCA10), recycled coarse aggregates 20 mm (RCA200), admixture (AD), and water (W), and the non-dimensional parameters include water-cement ratio (W/C), sand-aggregate ratio (S/A), water to total materials ratio (W/T), replacement ratio of recycled aggregate to natural aggregate by volume (RR), and aggregate to cement ratio (A/C). Following, the performance of each expressed data-driven model in predicting the 28 days compressive strength of concrete is presented.

4.1.1. Multiple Linear Regression model (MLR)

In the MLR model, the data are divided into two subsets of training and test. The proportions of training and testing are characterized based on the fact that the general structure of the model is constructed with respect to the training data set. Therefore, the amount of data in the training set plays a significant role. The total number of specimens was equal to 257 in which 85% of them (i.e. 218 specimens) were chosen for the training step, and 15% of them (i.e. 39 specimens) were selected for the test step. Fig. 3 shows the relationship between the measured and predicted compressive strength of the MLR model for the test step.

As it is shown in the figure, the R^2 value of the test step in MLR model is determined as 0.6085. In addition, the SSE and MSE are calculated as 3880.67 and 99.504, respectively. To conclude, MLR model did not show the high level of capability in predicting the 28 days compressive strength of concrete. This might be due to the fact that there is nonlinear relationship between the studied parameters and MLR model is mostly able to find out the linear relationship between the response and predictor variables.

4.1.2. Artificial Neural Network model (ANN)

In the ANN model, the data are divided into three subsets of training, validation, and test. The proportions of training, validation, and testing are characterized based on the fact that the general structure of the model is constructed based on the training data set. The total number of specimens were equal to 257 in which 70% of them (i.e. 179 specimens) were chosen for training step, 15% of them (i.e. 39 specimens) were selected for the validation step, and 15% of them (i.e. 39 specimens) were selected for the test step. In addition, the sigmoidal tangent function was chosen for hidden nodes. Different algorithms were tried to find the most suitable one, and among all of them, the Levenberg–Marquardt (LM) algorithm was selected. The ANN model was tested only with one hidden layer. Furthermore, in order to approximate the number of hidden nodes in the hidden layer, the experimental formula shown in Eq. (10) was used Sajedi and Huang, 2015a.

$$N_H <= 2N_1 + 1 \tag{10}$$

In which N_H is the maximum number of nodes in the hidden layer and N_1 is the number of inputs. Therefore, in this study, based on the number of input variables which was equal to 14, the maximum number of nodes in the hidden layer was chosen as 29. The structure of the ANN modeling in Matlab environment (Nazari and Khalaj, 2012) with 14 input parameters, 29 hidden nodes in the hidden layer, and one output parameter [14:29:1:1] is shown in Fig. 4.

Figs. 5 and 6 show the relationship between the measured and predicted compressive strength of the MLR model for the training and validation steps, respectively. R^2 is a statistical estimation to show how close the measured and predicted values are to each other. As shown in the figures, in both the training and validation step, the model presents desirable results in case of R values.

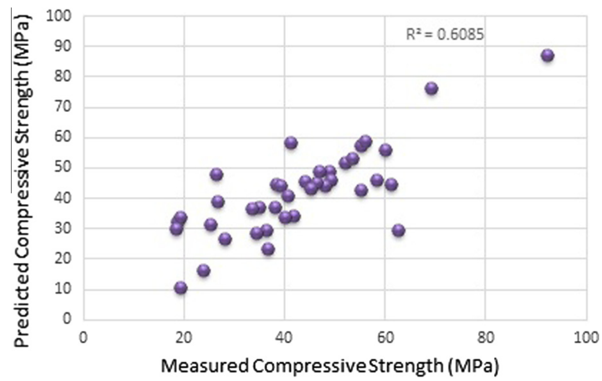

Figure 3. Relationship between the measured and predicted compressive strength of the test step of the MLR model.

In addition, in order to determine the performance of the model, the coefficient of determination (R^2) is evaluated for the test step, shown in Fig. 7.

As shown in the Fig. 7, the coefficient of determination for the testing of the ANN model is determined as $R^2 = 0.9185$. In addition, the SSE and MSE are determined as 770.94 and 19.77, respectively. To conclude, the ANN model is efficient in estimating the compressive strength of concrete, as compared to MLR.

4.1.3. Adaptive Neuro-Fuzzy Inference System (ANFIS)

In this study, the ANFIS modeling was performed in Matlab software and the proportions of training, validation (check), and testing were selected the same as the ones selected for ANN modeling. Fig. 8 shows the measured and predicted data for 28 days compressive strength of concrete for the training step. Fig. 8 demonstrates good coincidence of target and output data which indicate the capability of the ANFIS model.

In addition, Fig. 9 shows the relationship between the measured and predicted compressive strength for the testing of the ANFIS model. The coefficient of determination (R^2) shows the level of capability of the ANFIS model in predicting the 28 compressive strength of concrete.

As it is shown in the figure, the coefficient of determination for the test step of the ANFIS model is determined as $R^2 = 0.9075$. In addition, the SSE and MSE are determined as 992.67 and 25.45, respectively. To conclude, the ANFIS model is found to be capable in estimating the compressive strength of concrete with satisfactory performance.

4.1.4. Comparison of results of MLR, ANN, and ANFIS

In recent years, scientists have performed different investigations on various types of civil engineering materials, especially concrete and cement (Sajedi and Huang, 2015b; Khademi et al., 2015b; Bahari et al., 2016, 2012b;

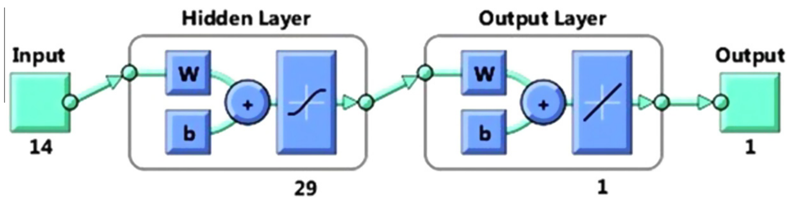

Figure 4. Structure of ANN model in Matlab environment with 14 input parameters, 29 hidden nodes in the hidden layer, and one output parameter.

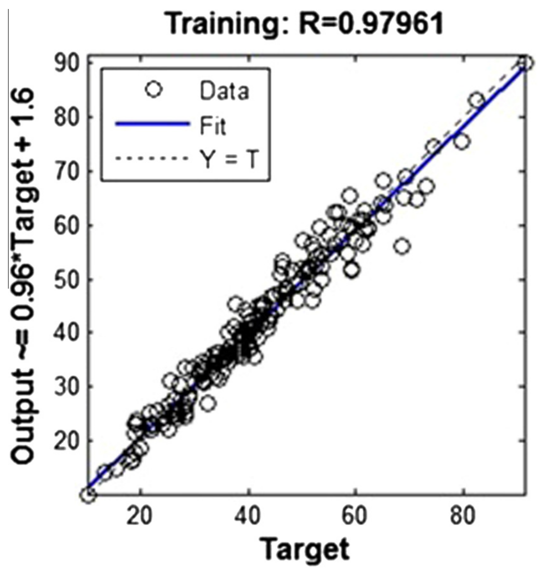

Figure 5. Relationship between the measured and predicted compressive strength of the training step of the ANN model.

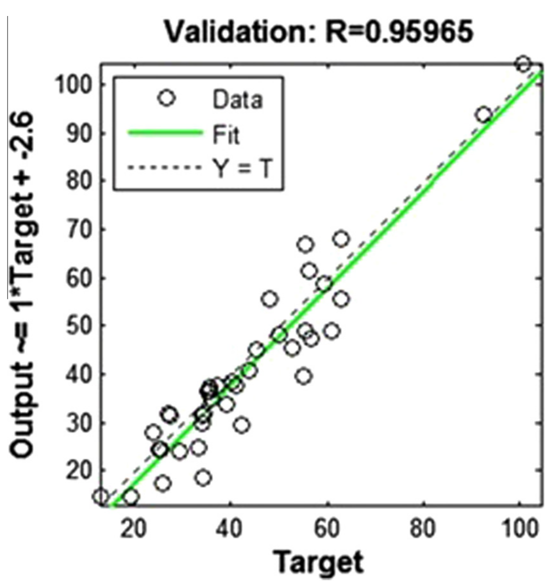

Figure 6. Relationship between the measured and predicted compressive strength of the validation step of the ANN model.

Hawkins et al., 2012; Nikoo et al., 2015b; Vu-Bac et al., 2015). The 28 days compressive strength of concrete is assumed as the standard compressive strength of concrete, and therefore, in both the engineering decisions and concrete constructions, estimating the compressive strength

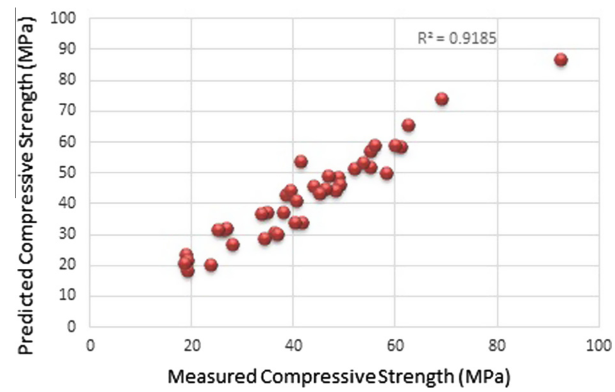

Figure 7. Relationship between the measured and predicted compressive strength of the test step of the ANN model.

of concrete is a significant fact. In this paper, the performance of MLR, ANN, and ANFIS on predicting the 28 days compressive strength of concrete based on coefficient of determination (R^2) and the sum of squared errors (SSE) is studied. The higher values of R^2 imply the higher capability of the model in prediction purposes. The values of R^2 and SSE for all the three models are shown in Table 3.

As it is illustrated in the Table, R^2 and SSE values act inversely. ANN model has the higher value of R^2 as compared to ANFIS and MLR. Therefore, ANN model is found to be the most efficient model in predicting the 28 compressive strength of concrete.

In addition, according to the table, it can be concluded that both the ANN and ANFIS models are capable enough in predicting the 28 days compressive strength of concrete. However, ANN outperforms ANFIS in the same prediction purposes. On the other hand, MLR model is found to be not reliable enough in predicting the 28 days compressive strength of concrete. The higher accuracy of ANN and ANFIS models in comparison to the MLR model may be due to the nonlinear relationship between the parameters which can be presented better by Ann and ANFIS. Normally, the MLR is a suggested model for proposing the preliminary mix design, and for higher accuracy necessities, the ANN and ANFIS models are recommended.

4.2. Sensitivity analysis

According to (Vu-Bac et al., 2014) sensitivity analysis (SA) is the investigation of how much model output parameters are influenced by changes in model input

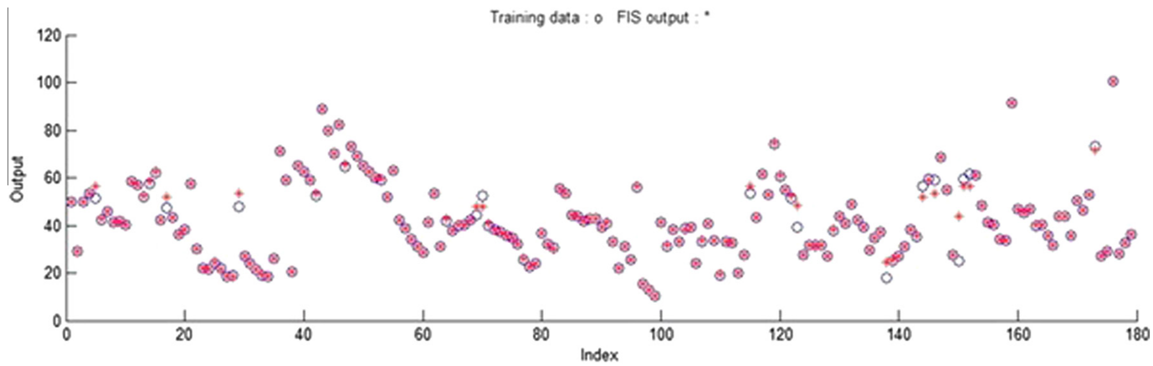

Figure 8. Comparison between the "Target" and "Output" parameters for "Training" step in ANFIS model.

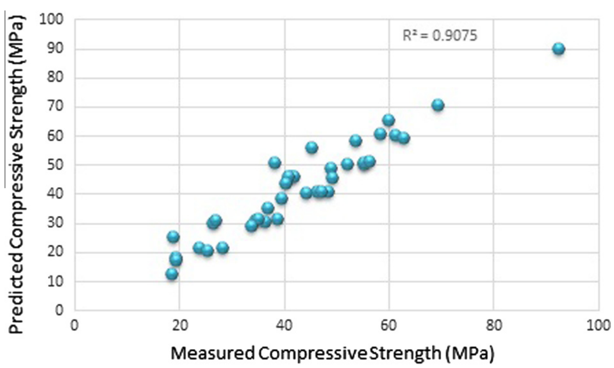

Figure 9. Relationship between the measured and predicted compressive strength of the test step of the ANFIS model.

parameters. In this study, the sensitivity analysis is performed on the data using ANN and ANFIS models, which were proved capable enough in the prediction purposes in the last section. In this research, the sensitivity analysis is performed from two different sides of views; (1) Sensitivity analysis based on efficiency of each individual input parameter on the output value, and (2) Sensitivity analysis based on efficiency of number of input parameters on the output value. Both are discussed comprehensively in the following.

4.2.1. Sensitivity analysis based on efficiency of each individual input parameter on the output value

In this section, the sensitivity analysis is performed based on the effect of each individual non-dimensional input parameter on the output value. In other words, in order to understand the correlation of each input parameter with the output parameter using ANN and ANFIS models, ANN1, and ANFIS1 were constructed based on the raw data as their input parameters. In addition, in ANN2 and ANIS 2, (S/A) was added as an additional parameter to the already existing ones in ANN1 and ANFIS1. Therefore, the effect of (S/A) on the prediction accuracy of the model was investigated. In the same way, all the other non-dimensional elements i.e. (W/C), (W/T), (A/C), (R/R) were added to ANN1 and ANFIS 1 individually and constructed in a separate network. The details of these ANN and ANFIs models are shown in Table 4.

4.2.1.1. Sensitivity analysis using ANN model. Figs. 10–15 show the relationship between the target and output compressive strength of ANN1 to ANN6, respectively, for both the training and validation steps. According to these figures, the performance of ANN1 to ANN6 is shown based on correlation coefficient (R).

Table 3
R^2 and SSE and MSE values for MLR, ANN, and ANFIS models.

Data-driven model	Coefficient of determination (R^2)	Sum of squared errors (SSE)	Mean squared error (MSE)
MLR	0.6085	3880.67	99.5043
ANN	0.9185	770.94	19.7676
ANFIS	0.9075	992.67	25.4530

Table 4
Characteristics of ANN and ANFIS models based on efficiency of each individual input parameter.

Input parameter	ANN model	ANFIS model
C, NFA, RFA, NC20, NC10, RCA20, RCA10, AD, W	ANN1	ANFIS1
C, NFA, RFA, NC20, NC10, RCA20, RCA10, AD, W, A/C	ANN2	ANFIS2
C, NFA, RFA, NC20, NC10, RCA20, RCA10, AD, W, S/A	ANN3	ANFIS3
C, NFA, RFA, NC20, NC10, RCA20, RCA10, AD, W, W/T	ANN4	ANFIS4
C, NFA, RFA, NC20, NC10, RCA20, RCA10, AD, W, R/R	ANN5	ANFIS5
C, NFA, RFA, NC20, NC10, RCA20, RCA10, AD, W, W/C	ANN6	ANFIS6

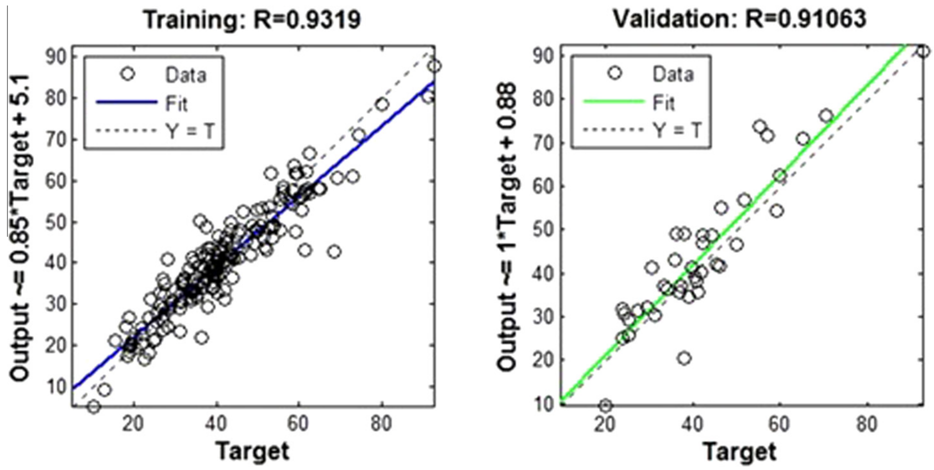

Figure 10. Relationship between the target and output values for training and validation steps in ANN1.

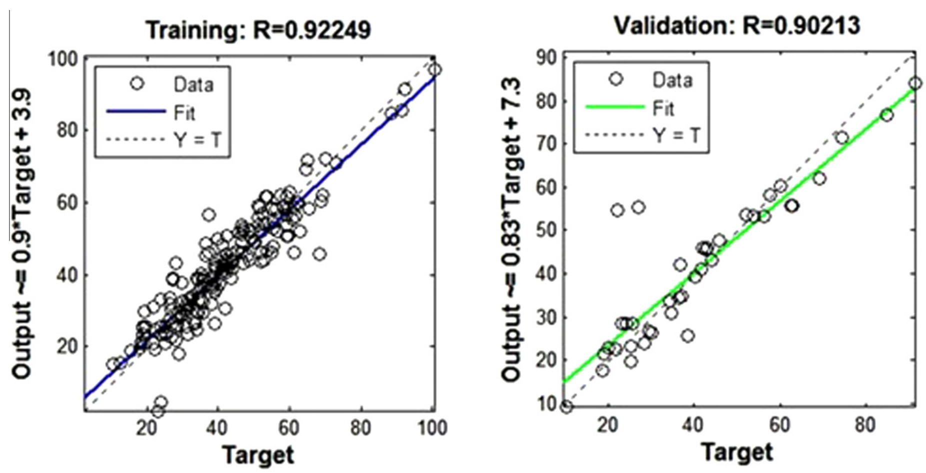

Figure 11. Relationship between the target and output values for training and validation steps in ANN2.

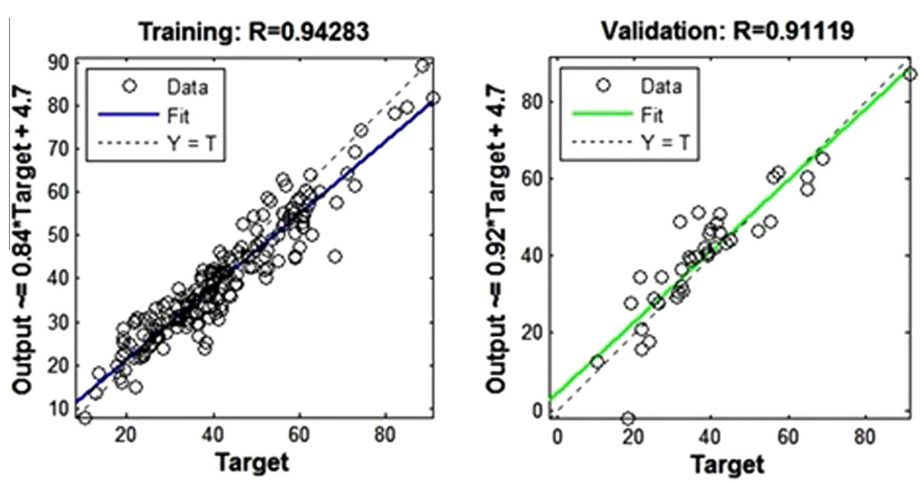

Figure 12. Relationship between the target and output values for training and validation steps in ANN3.

In addition, the results of the sensitivity analysis for ANN for test step based on coefficient of determination (R^2), the sum of squared errors (SSE), and the mean squared error (MSE) are shown in Table 5.

As it is shown in the table, when SA and RR were added as non-dimensional parameters (ANN3 and ANN5) to the model with just raw data (ANN1), the accuracy of estimating the 28 days compressive strength increases. On the

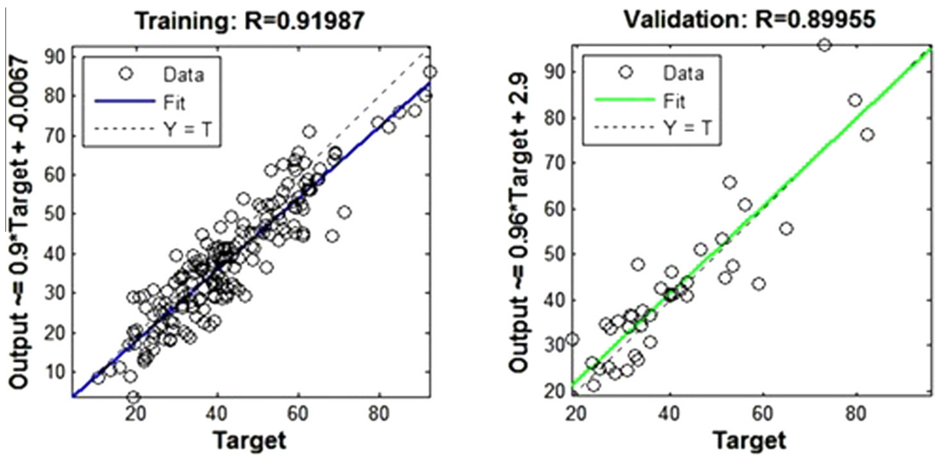

Figure 13. Relationship between the target and output values for training and validation steps in ANN4.

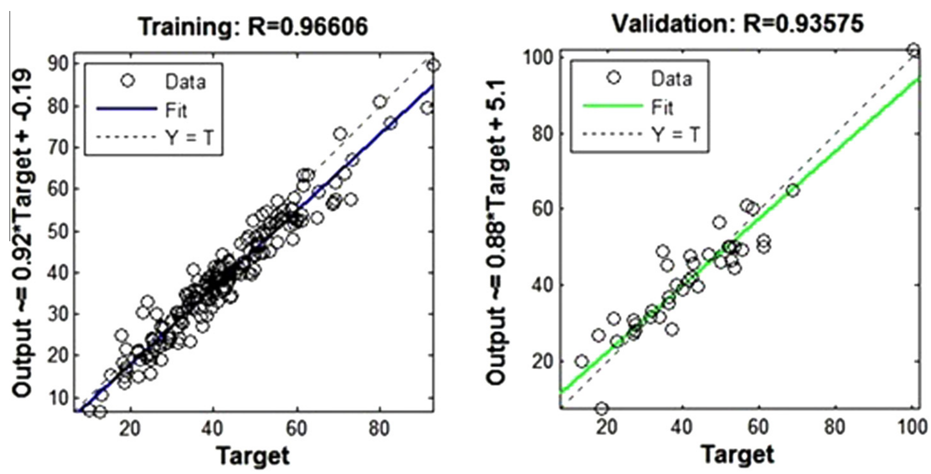

Figure 14. Relationship between the target and output values for training and validation steps in ANN5.

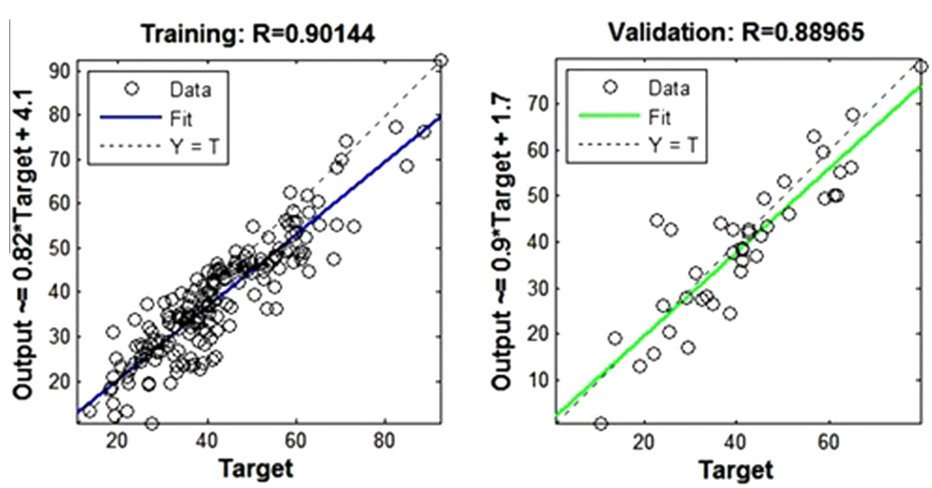

Figure 15. Relationship between the target and output values for training and validation steps in ANN6.

other hand, adding other non-dimensional parameters like A/C, W/T, and W/C (ANN2, ANN4, ANN6) to the model with raw data (ANN1) has an inverse impact on the accuracy of estimating the 28 days compressive strength of concrete which might be due to the duplication of the information.

Table 5
Values of R^2, SSE, and MSE for Test Step of ANN1 to ANN6.

Model number	Coefficient of determination (R^2)	Sum of squared errors (SSE)	Mean squared error (MSE)
ANN1	0.9086	987.1835	25.3124
ANN2	0.9059	1023.276	26.23785
ANN3	0.9132	981.5367	25.16761
ANN4	0.9050	1036.297	26.57172
ANN5	0.9151	959.39	24.59974
ANN6	0.9009	1091.0940	27.97677

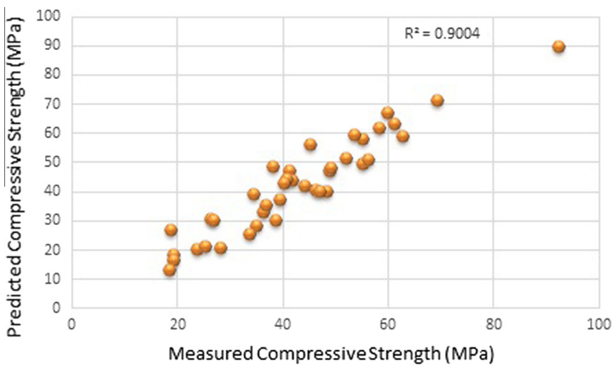

Figure 16. Relationship between the measured and predicted compressive strength of the test step of the ANFIS1 model.

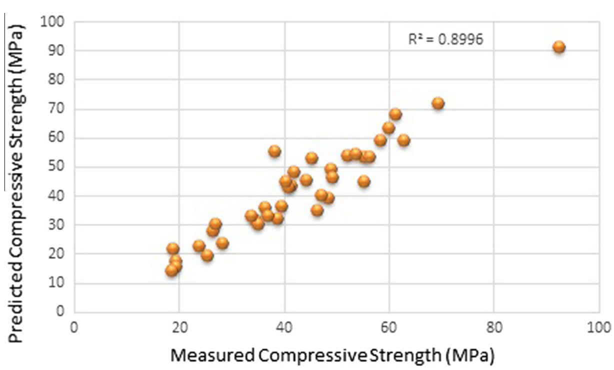

Figure 17. Relationship between the measured and predicted compressive strength of the test step of the ANFIS2 model.

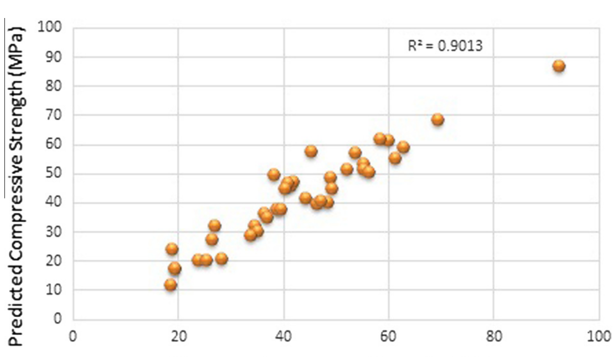

Figure 18. Relationship between the measured and predicted compressive strength of the test step of the ANFIS3 model.

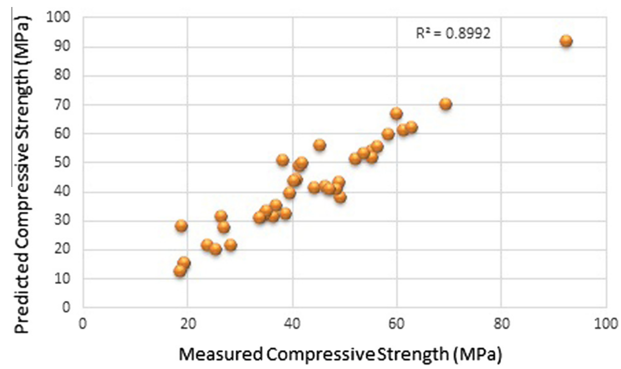

Figure 19. Relationship between the measured and predicted compressive strength of the test step of the ANFIS 4 model.

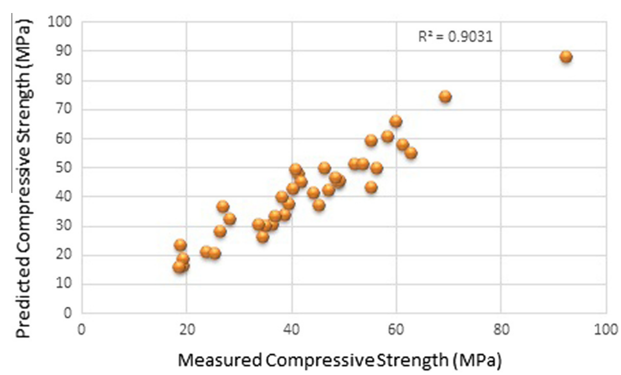

Figure 20. Relationship between the measured and predicted compressive strength of the test step of the ANFIS5 model.

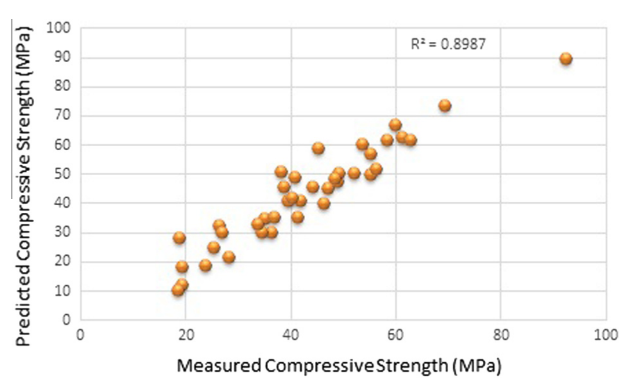

Figure 21. Relationship between the measured and predicted compressive strength of the test step of the ANFIS6 model.

Table 6
Values of R^2, SSE, and MSE for Test Step of ANFIS1 to ANFIS6.

Model number	Coefficient of determination (R^2)	Sum of squared errors (SSE)	Mean squared error (MSE)
ANFIS 1	0.9004	1095.052	28.07826
ANFIS 2	0.8996	1109.002	28.43595
ANFIS 3	0.9027	1020.8090	26.17459
ANFIS 4	0.8992	1116.678	28.63277
ANFIS 5	0.9031	1018.63	26.11872
ANFIS 6	0.8987	1130.014	28.97472

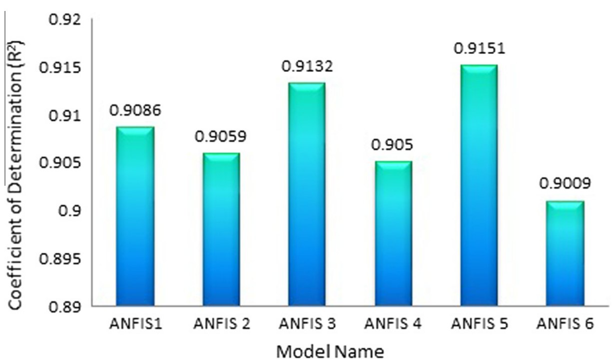

Figure 22. Coefficient of Determinations for the test steps of ANN1 to ANN6.

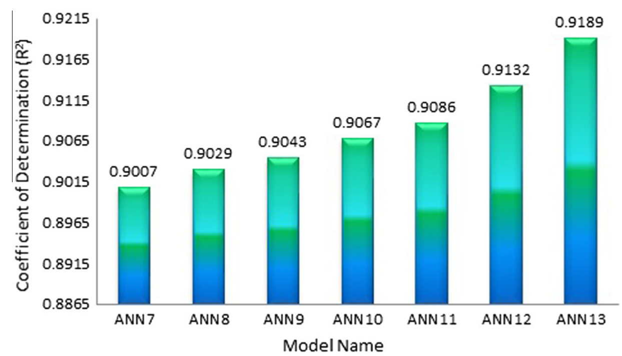

Figure 24. Coefficient of determinations for the test steps of ANN7 to ANN13.

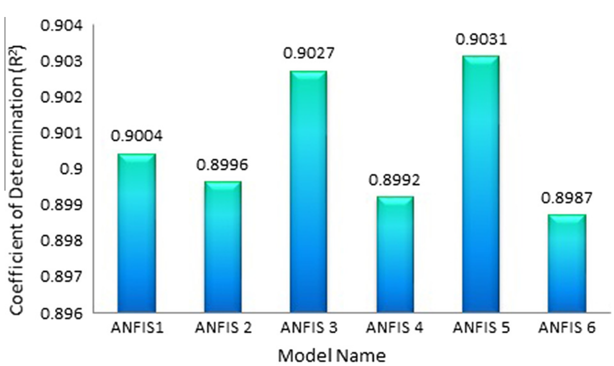

Figure 23. Coefficient of Determinations for the test steps of ANFIS1 to ANFIS6.

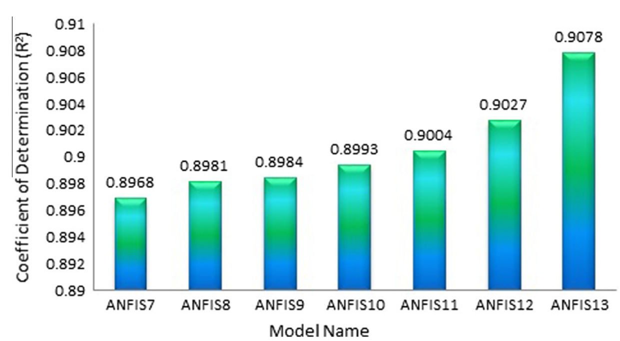

Figure 25. Coefficient of determinations for the test steps of ANFIS7 to ANFIS13.

Table 7
Characteristics of ANN and ANFIS models based on efficiency of number of input parameters on coefficient of determination.

Input parameter	ANN model	ANFIS model
C, NFA, RFA, NC20, NC10	ANN7	ANFIS7
C, NFA, RFA, NC20, NC10, RCA20	ANN8	ANFIS8
C, NFA, RFA, NC20, NC10, RCA20, RCA10	ANN9	ANFIS9
C, NFA, RFA, NC20, NC10, RCA20, RCA10, AD	ANN10	ANFIS10
C, NFA, RFA, NC20, NC10, RCA20, RCA10, AD, W	ANN11	ANFIS11
C, NFA, RFA, NC20, NC10, RCA20, RCA10, AD, W, S/A	ANN12	ANFIS12
C, NFA, RFA, NC20, NC10, RCA20, RCA10, AD, W, RR	ANN13	ANFIS13

4.2.1.2. Sensitivity analysis using ANFIS model. Figs. 16–21 show the relationship between the target and output compressive strength of ANFIS1 to ANFIS6, respectively, for the test step. According to these figures, the performance of ANFIS1 to ANFIS6 is shown based on coefficient of determination (R^2).

In addition, the results of the sensitivity analysis of ANFIS for the test step based on coefficient of determination (R^2), the sum of squared errors (SSE), and the mean squared error (MSE) are shown in Table 6.

As it is shown in the table, when the SA and RR were added as non-dimensional parameters (ANFIS3 and ANFIS5) to the model with just raw data (ANFIS1), the accuracy of estimating the 28 days compressive strength increases. On the other hand, adding other non-dimensional parameters like A/C (ANFIS2), W/T (ANFIS4), and W/C (ANFIS6) to the model with raw data (ANFIS1) has an inverse impact on the accuracy of estimating the 28 days compressive strength of concrete. This inverse impact on the accuracy of the result might be due to the fact that adding A/C, W/T, and W/C to ANFIs1 would result in the duplication of the information.

4.2.1.3. Results and discussion. Figs. 22 and 23 show the coefficient of determination of constructed ANN and ANFIS models, respectively. It is worth mentioning that all these models are constructed to investigate the efficiency of each individual input parameter on the output value.

As it is shown in the figures, adding SA and RA to the model with just the raw data would lead to increase in the accuracy of predicting the 28 days compressive strength of concrete. However, adding A/C, W/T, and W/C to the model with just the raw data would lead to decrease in the accuracy of estimating the compressive strength of concrete. This might be due to the fact that adding A/C, W/T, and W/C to raw data would lead to the duplication of information which would result in the reduction of the accuracy of predicting the 28 days compressive strength of concrete.

In addition, comparing all the ANFIS and ANN models, it is illustrated that performance of ANN model is more satisfactory in predicting the 28 days compressive strength of concrete in comparison to ANFIS in terms of coefficient of determination.

4.2.2. Sensitivity analysis based on efficiency of number of input parameters on the output value

As it was investigated, adding A/C, W/T, and W/C to the already existing raw data has a negative impact on the coefficient of determination. Therefore, in this part, in order to investigate the effect of the number of input parameters on the coefficient of determination, the raw data and the non-dimensional parameters which had positive impact on the coefficient of determination, i.e., RR and S/A are used as input parameters in this part. Different ANN and ANFIS models have been constructed to investigate the effect of number of input parameters on the coefficient of determination, shown in Table 7.

The coefficient of determination (R^2) for the test step of all the presented ANN and ANFIS models in Table 7 are shown in Figs. 24 and 25, respectively.

As it is shown in the figures, when the number of input variables increase, the coefficient of determinations increase. In other words, the more the number of input variables are, the more accurate the coefficient of determinations would be. It is worth mentioning that all these input variables should be independent from each other to have positive impact on the coefficient of determinations.

5. Conclusion

In this paper, three different data driven models, i.e., Artificial Neural Network (ANN), Adaptive Neuro-Fuzzy Inference System (ANFIS), and Multiple Linear Regression (MLR) were used to predict the 28 days compressive strength of recycled aggregate concrete (RAC). The following outcomes have been taken out from this research:

(1) MLR model with $R^2 = 0.6085$, SSE = 3880.67, and MSE = 99.5043 was found not to be efficient enough in predicting the 28 days compressive strength of concrete. This may be because of the nonlinear relationship between the studied elements and MLR model is mostly able to find out the linear relationship between the input and output variables.
(2) ANN model with $R^2 = 0.9185$, SSE = 770.94, and MSE = 19.7676 was found to be capable in estimating the 28 days compressive strength of concrete.
(3) ANFIS model with $R^2 = 0.9075$, SSE = 992.67, and MSE = 25.4530 was found to be talented in approximating the 28 days compressive strength of concrete.
(4) ANN and ANFIS models were found to be efficient in predicting the 28 days compressive strength of concrete, however MLR was found not to be capable enough in the same predicting purposes. In other words, MLR model is better to be used for preliminary mix design of concrete, and ANN and ANFIS are recommended in the mix design optimization and in the case of higher accuracy requirements. The advantage of ANN and ANFIS might be due to the fact that the relationship between the studied variables is nonlinear and these two models are more capable in determining the nonlinear relationship between the response and predictor variables.
(5) Although both the ANN and ANFIS models are capable enough to estimate the 28 days compressive strength of concrete, ANN was found more efficient than ANFIS.
(6) Adding non-dimensional parameters of SA and RA to the model with just the raw data would lead to increase in the accuracy of predicting the 28 days compressive strength of concrete.

(7) Adding non-dimensional parameters of A/C, W/T, and W/C to the model with just the raw data would lead to decrease in the accuracy of estimating the compressive strength of concrete. This might be due to the fact that adding A/C, W/T, and W/C to raw data would lead to the duplication of information which would result in the reduction of the accuracy of predicting the 28 days compressive strength of concrete.
(8) Increase in the number of independent variables would result in an increase in the accuracy of the model.

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