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# Prediction of the Compressive Strength of Concrete Containing Bentonite using Artificial Neural Networks

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## ABSTRACT

*Artificial neural systems are being adopted recently to simulate some of the numerous events in the fields of civil engineering. The research aims to create a model with the artificial neural networks (ANN) to predict the influence of bentonite as a partial substitute of cement on the concrete's compressive strength. The model in (ANN) for forecasting the compressive strength of concrete comprising bentonite was developed at the ages of 3, 7 and 28 days. 200 experimental samples from 26 different mix proportions of concrete were used from the selected literature to create, train, and test the model. The data employed in the multilayer feed-forward neural networks model were organized in an arrangement of seven input variables constituting the input layer neurons, a single hidden layer with ten neurons, and the compressive strength values at 28 days as a single neuron in the output layer in a two-layer ANN model architecture. As indicated in the various performance evaluations after the training, validation, and testing of the data, the neural networks possess credible ability for forecasting the compressive strength of concrete containing bentonite at 3, 7, and 28 days.*

**Keywords:** *ANN, multilayer feed forward networks, back propagation algorithm, MATLAB.*

## INTRODUCTION

The concrete utilization of hydraulic cement has increased rapidly over the years. About 7% of the global $CO_2$dischargesemanate from the manufacturing of cement most especially in the production of clinker [1].A reduction in the usage of cement in concrete is necessary to limit the emissions of $CO_2$into the natural environment. The utilization of pozzolanic materials will lessen the applications of hydraulic cement in concrete. The application of cement in concrete will be lessen by the use of artificial or industrial pozzolans like fly ash, Ground Granular Blast Furnace Slag (GGBS), silica fume, etc. as replacement materials to cement [2].The common practice nowadays is the utilization of pozzolans like fly ash in concrete manufacture.

Coal-based thermal power plants generate most of the fly ash [3]. High cost is involved to generate electricity through thermal plants relative to other power generation sources such as renewable energy sources etc. Enormous volume of $CO_2$ discharges is generated into the atmosphere by the thermal power plants. A lot of damage is caused as a result of fly ash production. Hence, the need to source for the use of harmless natural pozzolanic materials becomes necessary. Limited investigative studies were carried out by researchers in the replacement of cement in concrete by the application of bentonite. Bentonite is an environmentally harmless pozzolanic material that does not constitute an adverse effect on the environment [4]. Bentonite is an inorganic clay which displays slight swelling characteristics and conforming to pozzolanic behavior requirements [5]. According to Alkaya and Esener [6], bentonite isused in areas such as foundry bonds, drilling fluids, adhesives, adsorbents, ceramic and bleaching earths, etc. Mirza [7] experimented on bentonite substitution of cement in concrete. Sufficient studies were conducted by various researchers across the globe. Experimental outcomes showed certain trends associated with the application of bentonite. S.Targan et al. [8] submitted that the partial substitution of cement by bentonite resulted in the hastening of the cement setting time. Bentonite consists of metakaolin clay, a clay that had passed through the process of heat to form a powder and comprises an elementary material called montmorillonite which influences its properties. One of the finest extensive clays is bentonite which is usually adopted as a grease for piles insertion in bore wells and footings. Bentonitic clay can be applied as a binder due to its conformity to the pozzolanic characteristics [9]. Common examples of bentonite are sodium bentonite, calcium bentonite, and potassium bentonite, etc. Karthikeyan et al. [10] investigated the application on a partial substitute of cement by bentonite in concrete. The possible influence on several strength parameters of the ordinary Portland cement concrete was assessed by partially replacing it with bentonite. The outcomes showed that bentonite performed poorly at the initial stages in terms of strength enhancement relative to the natural concrete specimens. The percentage replacement by weight of cement for a concrete mix of grade 25 was 0%, 25% 30%, and 35%. It was discovered that at 28-days for 30% bentonite replacement of cement, the compressive, splitting tensile, and flexural strengths attained 19.55%, 2.72%, and 8.07% increase compared with the natural concrete. Also, at 28-day, 30% replacement of cement by bentonite gradually enhanced the flexural strength by 8.07%. the increment in the percentage replacement resulted in the decline in the compressive strength outside 35% as a result of the enhancement of the water-cement ratio by 23.3% relative to the natural concrete. The percentage extensions of the samples produced with partial replacement of cement by bentonite maintain allowable limits. Therefore, the materials satisfied the safety requirements for construction applications. It was also submitted that the durability and strength of concrete are improved with the use of bentonite. Bentonite is usually existing in numerous types and colors (e.g. greenish-brown and grayish-green) according to a few researchers [11].

According to Reddy et al. [12], strength disparity was detected for a similar amount of bentonite mix. This was attributed to the different sources of bentonite assemblage which resulted in strength variations as stated by numerous researchers. One other limitation according to Poon et al. [13] is the influence on the reactivity of clay due to variation in its mineralogy. Simulating or optimization models built on investigational or laboratory experimental data can forecast with a satisfactory margin of error the impact of bentonite in the replacement of cement in concrete performance to enhance the cost efficiency, reduce the investigation time and quantity of material. Artificial neural networks as an example of such models is an artificial intelligence system which learns through instance and can be adopted in a case where are tasks and problem database.ANN has demonstrated to be of enormous solution to simulating complex and difficult processes to an acceptable level of accuracy. It is also an influential instrument that provides credible outcomes to difficult problems compared with the results provided by the use of normal methods including multiple regression models without overturning them [14].The input and the outputs variables are used in carrying the modeling without several limitations on the input values [15]. ANN has been displayed to model both nonlinear and intricate associations between variables influencing the compressive strength concrete comprising of silica and/or fly ash [16-19],the granulated blast furnace slag concrete compressive strength [20], the natural concrete compressive strength[21-28], the high-performance concrete compressive strength [29] and the high strength concrete compressive strength [30]based on some published researches. Natural techniques for forecasting concrete compressive strength are predominantly numerical analysis dependent over which both the nonlinear and the linear regression calculations are developed for prediction [31]. Nevertheless, the selection of suitable regression calculation entails systemic approach and skill due to its complex nature. The goal of this study is to evaluate the possibility of using artificial neural networks in forecasting the compressive strength of concrete containing pulverized bentonitic clay (PBC) based on the data obtained from selected research works.

## Artificial Neural Networks

The investigation of biological neural networks stirred up the concept of artificial neural networks and the ANN tool lead to a commanding instrument used in data mining purposes [17].ANN is modeled based on the human brain mechanisms. The development of this technique was founded on the composition of synapses and neurons of the human brain. The human brain consists of interrelated neurons transferring signals utilizing the synapses to one another. Artificial neural networks are corresponding and dispersed schemes made up of the normal processing components and the artificial neurons, which similarly compute exact arithmetic performances to the construction of the human brain resulting in an improved efficiency relative to the normal models [15].

ANN architecture consists of five primary components which are the inputs, weights, sum function, activation capacity, and outputs. Data sources are data that go into the neuron from different neurons or the outside world. The weights display the impact of an information set or another procedure component. The sum function computes the impacts of the neuron inputs and weights completely [32], while the activation function analyses the clear input gotten from the sum function and establishes the output of the cell according to Haykin [33], the neuron is the component of data procedure in an artificial neural network, which comprises of:

- Synaptic weights $w_{km}$ duplicated assign $x_m$ in a neurotransmitter's input m associated with neuron k
- A calculator that adds up the inputs, weighted by the particular neuron's synapses, in which the contacts create a direct combination procedure.
- An activation function f(.), that confines the neuron output amplitude. The scope of standardized output amplitude can be [0,1] or otherwise [1,1] as outputs from the tan axon function.
- Bias, administered outwardly, denoted by $b_k$, which raises or reduces the impact of the activation function. Fig. 1 Establishes how the data is managed over a solitary neuron. Arithmetically, a neuron k can be defined by the equations shown below:

$$U_k = \sum W_{km} \; X \, x_m \qquad (1)$$

And

$$y_k = f(u_k + b_k) \qquad (2)$$

$x_1$, $x_2$, ......$x_m$ constitute the inputs; $w_{k1}$, $w_{k2}$...$w_{km}$ constitute the neuron weights k; $u_k$ constitutes the linear calculator outcome owing to inputs; $b_k$ constitutes the bias; $f(u_k + b_k)$ constitutes the activation function; $y_k$ constitutes the outcome.

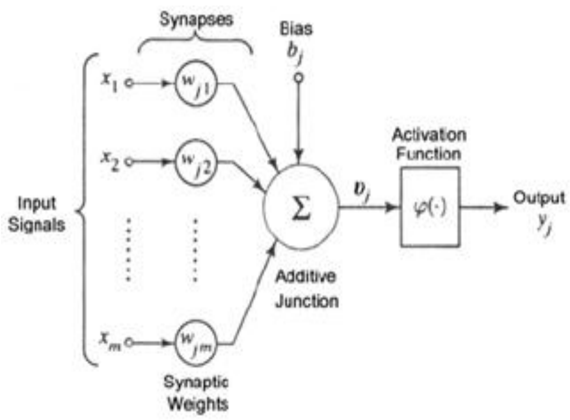


**Fig1.** *Artificial Neural model [33]*

In total, the hyperbolic tangent function in multilayer model remains the most adopted activation function. The outcome neuron is designed based on Eq. (3).

$$y_k = f(u_k + b_k) = tgh\,[\alpha.(u_k + b_k)] \qquad (3)$$

where $\alpha$ is the constant parameter used to regulate the gradient of the semi-linear curve. The tan axon function characterized by Eq. (3) regulates outcomes on the intermission [1,1].

Nascimento Jr. and Yoneyama [34] submitted that a linear function exists which is the modest calculational part where the bias can be construed as additional weight approaching from a component whose outcome is continually 1 as denoted by the Eq. (4).

$$y_k = f(u_k + b_k) = [\alpha.(u_k + b_k)] \qquad (4)$$

ANN modeling establishes the data flow and network-style or architecture. This may comprise a solitary layer or multilayer according to Kewalramani et al. [27]. An input layer, hidden or not hidden layer and an outcome layer are presented in the architecture of ANN. The network construction relates to a feed-forward network i.e. the outcomes are dependent on the present inputs only as regards the data movement [15]. The ANN structure that employs multilayer architecture and offers feed-forward data flow remains a frequently technique. It is applied in virtually all spheres involving artificial intelligence concept [21]. The two analyzing phases representing a very diverse period of the process which are involved in the neural network and are used at varying operation points are the training and testing respectively [14]. The suitable training technique produces weights adjustments [35]. Supervised methods that employ the delta rule as an algorithm and its overview of multilayer networks that constitute the back-propagation algorithm remain the most frequently used training procedures [15]. The gradient fall method to limit the fault for a definite training design through the weights' modifications by a little quantity per time is the back-propagation algorithm. The weight which may comprise vital information after training is haphazard and meaningless before training [35].The weights signify the level of impact that the individual input variable displays as regards the output variable. How the system responds to an input with the original construction not being affected constitutes the testing procedures [14].

## Feed-Forward Networks

The neurons are organized in layers, and all the neurons in the respective layer consists of networks tothe entire neurons in the subsequent layer in a feed-forward neural network [36]. Still, there is no linking among neurons of the similar layer or the neurons not in succeeding layers. The feed forward network comprises a single input layer, one or two hidden layers, and one output layer of neurons [37].

Linked with the individual joining amid these artificial neurons, a weight worth is expressed to epitomize the joining weight [36]. Fig. 2 displays a characteristic construction of a multilayer feed-forward neural network consisting of an input layer, dual hidden layer, and an outcome layer. The input layer accepts input data and forwards it on the hidden layer(s) neurons, which then relay the info towards the output layer. The forecast of the net for the matching input is provided at the input nodes. The Individual neuron in the network acts similarly as shown in Eqs. (5) and (6). There exists no consistent technique for determining the quantity of neural components essential for a specific challenge. This is determined according to knowledge and limited trial is mandatory to regulate the greatest arrangement of the network [37]. The multilayer feed-forward kind of Artificial neural networks as shown in Fig. 2 is adopted in this study. The inputs and output variables are regularized within the range of 0–1 in a feed-forward network.

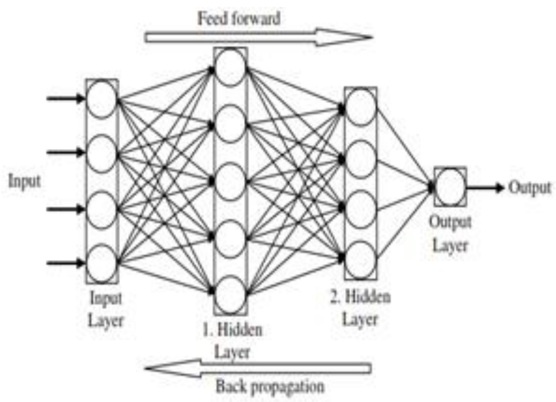


**Fig2.** *A characteristic construction of a multilayer feed-forward neural network [38]*

$$(net)_j = \sum_{i=1}^{n} w_{ij}\ o_i + b \qquad (5)$$

$$o_j = f(net)_j = \frac{1}{1 + e^{-\propto (net)_j}} \qquad (6)$$

## The Back-Propagation Algorithm

Back propagation algorithm is a slope descent method to diminish the error for a specific training outline in which it regulates the weights by a slight quantity at a period as one of the most famous training algorithms for the multilayer perceptron [39-41]. The network error is transmitted rearward from the outcome layer to the input layer, and the weights are regularized through few training tactics to lessen the network error to a satisfactory grade [42]. The $r^{th}$ example error is computed by Eq. (7):

$$E_r = \frac{1}{2}\sum_j (t_j - o_j)^2 \qquad (7)$$

Here $t_j$ is the outcome anticipated at neuron $j$ and $o_j$ is the output forecast at neuron $j$. The outcome $o_j$ is a function of synaptic power and outputs of the preceding layer as offered in Eqs. (5) and (6) [37].

The training comprises varying the weights to diminish this error function in a slope descent method. The error amid the network outcome and the favorite outcome quantities is computed by utilizing theso-called general delta rule in the back-propagation stage, [43], and weights between neurons are restructured from the output layer towards the input layer by Eq. (8) [44].

$$w_{ij}(m+1) = w_{ij}(m) + \eta\left(\delta_j + o_j\right) + \beta w_{ij}(t) \qquad (8)$$

Here, $\delta_j$ is the error sign at a neuron $j$, $oj$ is the neuron $j$ outcome, $m$ is the iteration figure, and $\eta$, $\beta$ are termed training proportion and motion proportion, individually. $\delta_j$ in Eq. (8) can be computed by utilizing the error function Er fractional derivative in the output layer and another layer, correspondingly, by Eqs. (9) & (10) [37,44]

$$\delta_j = o_j\left(t_j - o_j\right)\left(1 - o_j\right) \qquad (9)$$

$$\delta_j = o_j\left(1 - o_j\right)\sum_k \delta_k\, w_{kj} \qquad (10)$$

Now, the kth layer refers to the higher level of the $jth$ layer [44]. The processes above are recurrent for the respective instance and all the neurons till an acceptable junction is attained for the entire samples available for the training set [37]. The learning procedure is effectively accomplished after the iterative aspect has joined. The linking weights are taken from the skilled network, to apply them in the recollection stage [44]. A multilayer feed-forward network is implemented for training resolve for the current investigation. A back-propagation algorithm is applied to lessen the error.

## Neural Network Model

A multilayer feed-forward neural network consisting of back-propagation algorithm was utilized in this study. The nonlinear sigmoid function was adopted in the concealed layer and the cell outcomes at the output layer. A multilayer artificial neural network construction was created. The age (AG), cement content (C), water (W), natural coarse aggregate (NCA), natural fine aggregate (NFA), water-cement ratio (W/C), and fineness modulus of cement (FM) constituted the input variables while the compressive strength (fc) value was adopted as the output in training and testing of the ANN established with a single architecture as observed in Fig. 3; a single hidden layer was carefully chosen. In the hidden layer, ten neurons were chosen based on its least absolute percentage error standards for training and testing data sets. Additional details concerning input and output parameters can be gotten from the research literature [10,12]. The limiting values of input and output parameters adopted in the ANN model are enumerated in Table 1.The neurons of adjoining layers are completely interrelated by weights in the ANN model. Lastly, the outcome layer neuron yields the network forecast as a consequence. Momentum and learning rate values were established for the model which was trained through repetitions. The quantities of parameters used in ANN are specified in Table 2. The skilled model was solitary tested with the input quantitates and the results generated were near experimental outcomes.

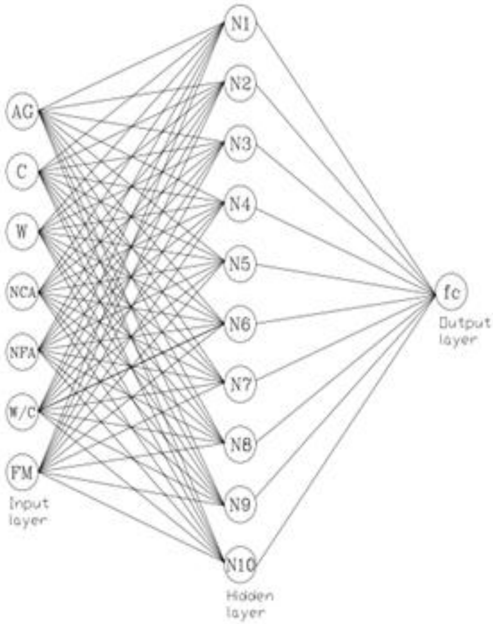


**Fig3.** *ANN Architecture used in the study*

**Table1.** *Parameters adopted in the Artificial Neural Network model*

| | Data applied in training and testing of the mode | |
|---|---|---|
| | Min. | Max. |
| *Input variables* | | |
| Age of sample (Day) | 3 | 28 |
| Cement (kg/m$^3$) | 288.34 | 447.00 |
| water | 191.50 | 197.00 |
| Natural coarse aggregate(kg/m$^3$) | 902.73 | 1180.40 |
| Natural fine aggregate(kg/m$^3$) | 537.27 | 671.86 |
| water/cement ratio | 0.43 | 0.66 |
| Fineness modulus of cement (%) | 4.50 | 8.00 |
| *Output variable* | | |
| Compressive strength (MPa) | 8.00 | 39.89 |

**Table2.**

The values of parameters used in the model

| Parameters | ANN model |
|---|---|
| Number of input layer neurons | 7 |
| Number of hidden layer | 1 |
| Number of hidden layer neurons | 10 |
| Number of output layer neuron | 1 |
| Momentum rate | 0.7 |
| Learning rate | 0.3 |
| Error after learning | 0.0002 |
| Learning cycle | 50 |

**Table3.** *Testing data sets for assessment of investigational outcomes with testing outcomesforecast from model*

| | Age | Cement content | Water | Natural coarse aggregate | Natural fine aggregate | Water cement ratio | Fineness modulus of cement | Compressive strength | Data source |
|---|---|---|---|---|---|---|---|---|---|
| S/N | AG(Day) | C(kg/m$^3$) | W(kg/m$^3$) | NCA(kg/m$^3$) | NFA(kg/m$^3$) | W/C | FM(%) | fu (N/mm$^2$) | Reference |
| 1 | 3 | 437.00 | 197.0 | 919.77 | 670.85 | 0.450 | 6 | 22.45 | [12] |
| 2 | 3 | 393.30 | 197.0 | 913.20 | 665.80 | 0.450 | 8 | 16.79 | [12] |
| 3 | 3 | 371.45 | 197.0 | 921.15 | 671.86 | 0.450 | 7.5 | 9.16 | [12] |
| 4 | 3 | 349.60 | 197.0 | 915.62 | 667.82 | 0.450 | 6 | 14.17 | [12] |
| 5 | 3 | 327.75 | 197.0 | 905.94 | 660.76 | 0.450 | 5 | 12.64 | [12] |
| 6 | 3 | 305.90 | 197.0 | 902.73 | 657.73 | 0.450 | 4.5 | 10.90 | [12] |
| 7 | 7 | 437.00 | 197.0 | 919.77 | 670.85 | 0.450 | 6 | 26.81 | [12] |
| 8 | 7 | 393.30 | 197.0 | 913.20 | 665.80 | 0.450 | 8 | 25.51 | [12] |
| 9 | 7 | 371.45 | 197.0 | 921.15 | 671.86 | 0.450 | 7.5 | 19.62 | [12] |
| 10 | 7 | 349.60 | 197.0 | 915.62 | 667.82 | 0.450 | 6 | 16.46 | [12] |
| 11 | 7 | 327.75 | 197.0 | 905.94 | 660.76 | 0.450 | 5 | 15.48 | [12] |
| 12 | 7 | 305.90 | 197.0 | 902.73 | 657.73 | 0.450 | 4.5 | 11.01 | [12] |
| 13 | 7 | 443.60 | 191.5 | 1180.40 | 537.27 | 0.432 | - | 18.00 | [10] |
| 14 | 7 | 332.70 | 191.5 | 1180.40 | 537.27 | 0.576 | - | 17.00 | [10] |
| 15 | 7 | 310.82 | 191.5 | 1180.40 | 537.27 | 0.616 | - | 20.00 | [10] |
| 16 | 7 | 288.34 | 191.5 | 1180.40 | 537.27 | 0.664 | - | 8.00 | [10] |
| 17 | 28 | 437.00 | 197.0 | 919.77 | 670.85 | 0.450 | 6 | 39.89 | [12] |
| 18 | 28 | 393.30 | 197.0 | 913.20 | 665.80 | 0.450 | 8 | 28.99 | [12] |
| 19 | 28 | 371.45 | 197.0 | 921.15 | 671.86 | 0.450 | 7.5 | 26.60 | [12] |
| 20 | 28 | 349.60 | 197.0 | 915.62 | 667.82 | 0.450 | 6 | 27.25 | [12] |
| 21 | 28 | 327.75 | 197.0 | 905.94 | 660.76 | 0.450 | 5 | 17.00 | [12] |
| 22 | 28 | 305.90 | 197.0 | 902.73 | 657.73 | 0.450 | 4.5 | 13.52 | [12] |
| 23 | 28 | 443.60 | 191.5 | 1180.40 | 537.27 | 0.432 | - | 25.00 | [10] |
| 24 | 28 | 332.70 | 191.5 | 1180.40 | 537.27 | 0.576 | - | 22.00 | [10] |
| 25 | 28 | 310.82 | 191.5 | 1180.40 | 537.27 | 0.616 | - | 30.00 | [10] |
| 26 | 28 | 288.34 | 191.5 | 1180.40 | 537.27 | 0.664 | - | 10.00 | [10] |

## Results and Discussion

The error established throughout the training and testing in the ANN model in this study is stated as a root-mean-squared (RMS) error and is computed by Eq. 11 [40, 41]

$$RMS = \sqrt{\frac{1}{n}\sum_{i}|t_i - o_i|^2}. \qquad (11)$$

The mean absolute percentage error (MAPE) and the absolute variance fraction ($R^2$), and) are computed using Eqs. (12) and (13), respectively [40,41,45,46]

$$\text{MAPE} = \left[\left(\frac{t_i - o_i}{o_i}\right)\right] * 100, \qquad (12)$$

$$R^2 = 1 - \left(\frac{\sum_i (t_i - o_i)^2}{\sum_i (o_i)^2}\right). \qquad (13)$$

Now, t is the target value, o is the outcome value, n is the number of examples in the data set. Numerous investigational data from two dissimilar bases [10,12] are deployed in the training and testing of the ANN model. 200 data of experiment outcomes were used for the study out of which 70% was used for training, and 15% each for validation and testing respectively.

The activation function and the training algorithm adopted are the sigmoid function and Levenberg-Marquardt respectively. The arrangement is realized using the MATLAB ANN tool kit. The selection of the network as regards the number of neurons in the hidden layer is built on the distribution of the error on the zero error and the network performance value. The number of neurons with less lopsidedness of the error histogram and with the best output value was carefully chosen to be the characteristic network.

All results gotten from experimental studies [10,12] i.e. regression of plots, performance evaluation, and forecast by utilizing the training and testing outcomes of ANN model 3, 7, and 28 days fc were specified in Figs. 4 and 5. The linear least-squares fit line, its calculation and the $R^2$quantities were revealed for the training validation and testing data in these figures. Similarly, inputs quantities and investigational outcomes with testing outcomes gotten from the ANN model were specified in Table 3.The values found from the training and testing in the ANN model are very nearer to the experimental outcomes. The testing stage result in Figs. 4 & 5 displays that the ANN model can generalize between input and output parameters with sensibly decent forecasts and minimum error margin.

The statistical data of the multiple R, fraction of variance ($R^2$), forall cases of training, validation, and testing were given as 0.9387and 0.8813 respectively as shown in Figs. 4 & 5. The Root-Mean Square (RMS), Mean Absolute Percentage Error (MAPE), and the Variance fraction ($R^2$) were also computed for all cases using equations 11, 12, and 13 respectively and the results are displayed in Table 4.

**Table4.** *The fc numerical values of the projected ANN model*

| *Numerical Values* | *ANN- (All cases of Training, Validation and Testing)* |
|---|---|
| *Multiple R* | *0.9387* |
| *Fraction of Variance-$R^2$* | *0.8813* |
| *Root Mean Square-RMS* | *2.8331* |
| *Mean Absolute Percentage Error-MAPE (%)* | *6.36* |

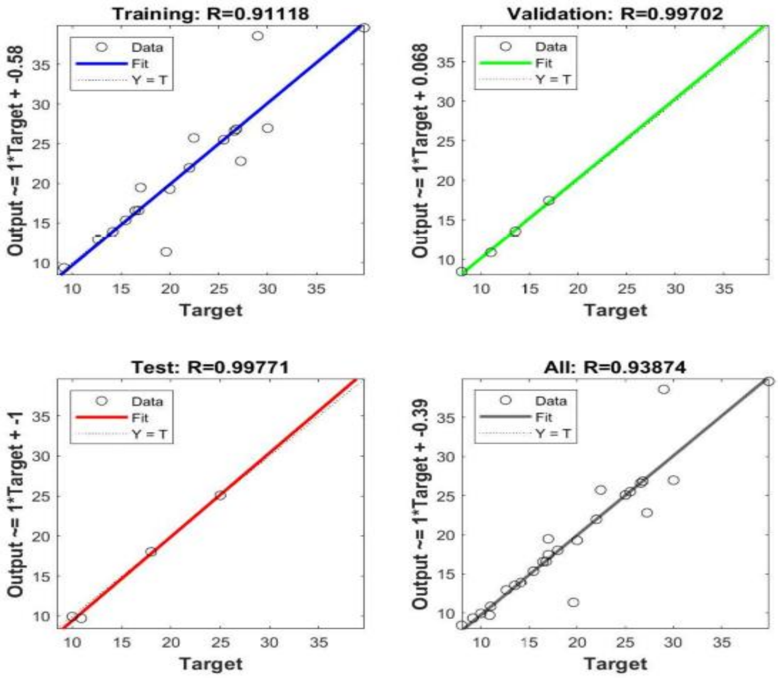


**Fig4.** *The regression of plots of training, validation, testing and all*

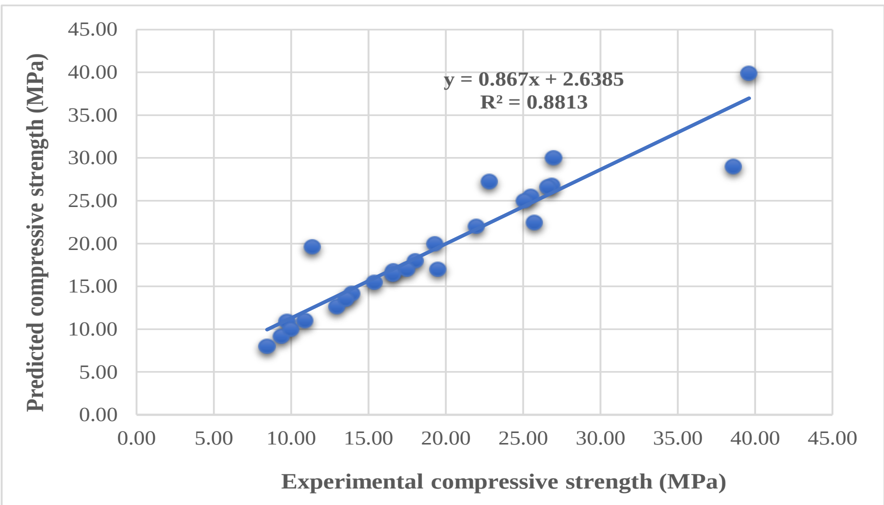


**Fig5.** *Evaluation of fc experimental outcomes with training outcomes of ANN model*

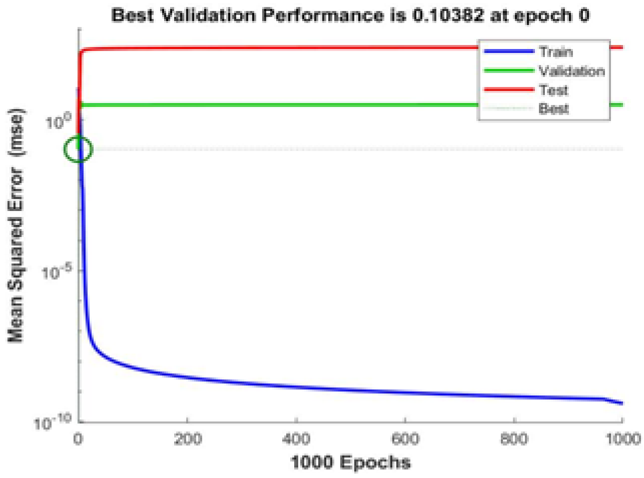


**Fig6.** *Performance evaluation of the training, validation, and testing*

All of the arithmetical data in Table 4 confirm that the projected artificial neural network model is appropriate and forecast the 3, 7, and 28 days fc values very near to the investigational values. Best validation performance is 0.10382 at epoch 0 as shown in Fig.6.

## Conclusions

ANNs are proficient in learning and simplifying from instances and practices. These enable artificial neural networks an influential instrument for resolving certain complex civil engineering difficulties. In this work, these helpful properties of artificial neural networks of a two-layer multilayer architecture were used to predict the 3, 7, & 28 days compressive strength values of concretes comprising of bentonite without trying any experiments. In the model created, a multi-layered feed-forward neural network with a back-propagation algorithm was applied consisting of seven neurons in a single input layer, ten neurons in a single hidden layer and one neuron in a single output layer. The model was trained with input and outcome data. The 3, 7, and 28days compressive strength values of concretes containing bentonite was created by utilizing only the input data in the trained model. The compressive strength quantities forecast from training and testing, for the ANN model, are very close to the experimental outcomes as shown by the statistical parameters of RMS, $R^2$, and MAPE computed for comparing investigational outcomes with artificial neural networks model. Consequently, compressive strength values of concretes comprising of bentonite can be forecast in the multilayer feed-forward artificial neural networks model without performing any laboratory tests in a fairly quick time with low error margins. This shows that the multilayer feed-forward artificial neural networks are realistic procedures for forecasting compressive strength of concrete comprising of bentonite.

## References

[1] Andrew, G.R.M. (2018). Global $CO_2$ emissions from cement production. *Earth Syst. Sci. Data*, **10**,195–217.

[2] Siddique, R. (2014). Utilization of industrial by-products in concrete. *Procedia Engineering*,**95**, no. Scescm. Elsevier B.V.,335–347.

[3] Nizar, K., Kamarudin, H., and Idris, M. S. (2007). Geopolymer lightweight aggregate View project Electrodes for Li-ion batteries View project.

[4] Akbar, J., Bashir, A., Mahummas, S., Salman, A., and Khan, S. (2013).Evaluating the effect of bentonite on strength and durability of High-performance concrete. *International Journal Of Advanced Structures And Geotechnical Engineering*, **2**(1): 1-5.

[5] Saba, S., Barnichon, J.D., Cui, Y.J., Tang, A.M., and Delage, P. (2014). Microstructure and anisotropic swelling behavior of compacted bentonite/sand mixture," *Journal of Rock Mechanics and Geotechnical Engineering*, Elsevier Ltd **6**(2):126–132.

[6] Alkaya, D., and Esener, B. (2011). Usability of sand-bentonite cement mixture in the construction of unpermeable layer,**6**(21): 4492–4503.

[7] Mirza, J., Riaz, M., Naseer, A., Rehman, F., Khan, A.N., and Ali, Q. (2009). Pakistani bentonite in mortars and concrete as low-cost construction material. *Applied Clay Science*, Elsevier B.V **45**(4):220–226.

[8] Targan, S., et al., (2002). Effects of supplementary cementing materials on the properties of cement and concrete. *Cement and Concrete Research*, **32**(10), 1551-1558.

[9] Siddique, R. (2014). Utilization of industrial by-products in concrete. 2nd International conference on sustainable civil engineering structures and construction materials. *Procedia Engineering*,**95**: 335 - 347.

[10] Karthikeyan, M., Ramachandran, P.R., Nandhini, A., and Vinodha, R. (2015). Application on partial substitute of cement by bentonite in concrete. *International Journal of ChemTech Research*, 8(11): 384-388.

[11] Akbar, J., Alam, B., Ashraf, M., Afzal, S., Ahmad, A., and Khan Shahzada. (2013). Evaluating the effect of bentonite on strength and durability of high-performance concrete. *International Journal of Advanced Structures and Geotechnical Engineering*,**2**(1):1–5.

[12] Reddy., G.V.K, Rao, V.R., and Reddy, M.A.K. (20179). Utilization of bentonite in concrete: a review. *International Journal of Recent Technology and Engineering (IJRTE)*,**7**(6C2):541-545

[13] Poon, C. S., et al., (2005). Compressive strength, chloride diffusivity and pore structure of high-performance metakaolin and silica fume concrete. *Construction and Building Materials*, 20(10): 858- 865.

[14] Oliveira Junior, H.A., Caldeira, A.M., Machado, MAS.,Souza, R.C., and Tanscheit, R. (2007). Computational Intelligence Applied to the Administrative, Economics, and Engineering in Matlab. New York: Thomson Learning.

[15] Braga, A.P., Carvalho, APLF., and Ludermir, T.B. (2000). Artificial neural networks: theory and applications. 2nd ed. Rio de Janeiro: LTC; 2000 [in Portuguese].

[16] Pala, M., Özbay, E., Öztas, A., and Yuce, M.I. (2007). Appraisal of long-term effects of fly ash and silica fume on compressive strength of concrete by neural networks. *Constr Build Mater*, **21**:384–94.

[17] Topçu, I.B., and Sarıdemir, M. (2008). Prediction of compressive strength of concrete containing fly ash using artificial neural networks and fuzzy logic. *Comput Mater Sci*, **41**:305–11.

[18] Özcan, F., Atis, CD., 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**:856–63.

[19] Saridemir, M. (2009). Prediction of compressive strength of concretes containing metakaolin and silica fume by artificial neural networks. *Adv Eng Softw*, **40**:350–5.

[20] Bilim, C., Atis, CD., Tanyildizi, H., and Karahan, O. (2009). Predicting the compressive strength of ground granulated blast furnace slag concrete using artificial neural network. *Adv EngSoftw*, **40**:334–40.

[21] Hong-Guang, N., and Ji-Zong, W. (2000). Prediction of compressive strength of concrete by neural networks. *CemConcr Res*.,**30**:1245–50.

[22] Fazel, Zarandi, M.H., Turksen, I.B, Sobhani, J., and Ramezanianpour, A.A. (2008). Fuzzy polynomial neural networks for approximation of the compressive strength of concrete. *Appl Soft Computing*, **8**:488–98.

[23] Lee, J.J., Kim, D., Chang, S.K., and Nocete, CFM. (2009). An improved application technique of the adaptive probabilistic neural network for predicting concrete strength. *Comput Mater Sci*, **44**:988–98.

[24] Sarıdemir, M., Topçu, IB., Ozcan, F., and Severcan, MH. (2009). Prediction of long-term effects of GGBFS on compressive strength of concrete by artificial neural networks and fuzzy logic. *Constr Build Mater*, 23:1279–86.

[25] Naderpour, H., Kheyroddin, A., and Amiri, G.G. (2010). Prediction of FRP-confined compressive strength of concrete using artificial neural networks. *Compos Struct*,**92**:2817–29.

[26] Madandoust, R., Ghavidel, R., and Nariman-Zadeh, N. (2010). Evolutionary design of generalized GMDH-type neural network for prediction of concrete compressive strength using UPV. *Comput Mater Sci*,**49**: 556–67.

[27] Kewalramani, MA., and Gupta, R. (2006). Concrete compressive strength prediction using ultrasonic pulse velocity through artificial neural networks. *Autom Constr*,**15**:374–9.

[28] Sobhani, J., Najimi, M., Pourkhorshidi, AR., and Parhizkar T. (2010). Prediction of the compressive strength of no-slump concrete: a comparative study of regression, neural network, and ANFIS models. *Constr Build Mater*,**24**: 709–18.

[29] Öztas, A., Pala, M., Özbay, E., Kanca, E., Çaglar, N., and Bhatti, M.A. (2006). Predicting the compressive strength and slump of high strength concrete using neural network. *Constr Build Mater*, **20**:769–75.

[30] Słonski, M. A.(2010). Comparison of model selection methods for compressive strength prediction of high-performance concrete using neural networks. *Comput Struct*, **88**:1248–53.

[31] Hong-Guang, N., and Ji-Zong, W. (2000). Prediction of compressive strength of concrete by neural networks. *CemConcr Res*, **30**:1245–50.

[32] Pala, M., Ozbay, E., Oztas, A., and Yuce, M.I. (2005). Appraisal of long-term effects of fly ash and silica fume on compressive strength of concrete by neural networks. *J. Constr. Build. Mater.*, 21: 384-394.

[33] Haykin S. (2001). Neural networks: principles and practice. Porto Alegre: Ed Bookman;[in Portuguese].

[34] Nascimento, CL, and Yoneyama, T. Artificial intelligence in control and automation. São Paulo: Edgard Blücher LTDA and FAPESP; 2000 [in Portuguese].

[35] Mata J. (2011). Interpretation of concrete dam behavior with artificial neural network and

multiple linear regression models. *Eng. Struct*, 33:903–10.

[36] Adhikary BB, Mutsuyoshi H. Prediction of shear strength of steel fiber RC beams using neural networks. *Constr Build Mater,* **20**(9):801–11.

[37] Mukherjee A, Biswas SN. (1997). Artificial neural networks prediction of mechanical behavior of concrete at high temperature. *NuclEng Design*, **178**(1),1–11.

[38] Sarıdemir, M. (2009). *Prediction of compressive strength of concretes containing metakaolin and silica fume by artificial neural networks. Advances in Engineering Software*, **40**(5), 350–355. DOI: 10.1016/j.advengsoft.2008.05.002

[39] Topçu _ IB, Sarıdemir., M. (2007). Prediction of properties of waste AAC aggregate concrete using artificial neural network. *Comp Mater Sci*, **41**(1):117–25.

[40] Topçu _ IB, Sarıdemir., M. (2008). Prediction of compressive strength of concrete containing fly ash using artificial neural network and fuzzy logic. *Comp Mater Sci*,**41**(3):305–11.

[41] Pala., M, Özbay., E, Öztas., A, and Yüce, MI. (2007). Appraisal of long-term effects of fly ash and silica fume on compressive strength of concrete by neural networks. *Constr Build Mater,* **21**(2):384–94.

[42] Demir., F. (2008). Prediction of elastic modulus of normal and high strength concrete by artificial neural network. *Constr Build Mater*, **22**(7),1428–35.

[43] Rumelhart., DE, Hinton., GE, William., RJ. (1986). Learning internal representations by error propagations. In: Rumelhart DE, McClelland JL, editors. Proceedings parallel distributed processing. foundations, vol. 1. Cambridge: MIT Press; 1986.

[44] Ince., R. (2004). Prediction of fracture parameters of concrete by artificial neural networks. *EngFract Mech*, 71(15):2143–59.

[45] Topçu., _ IB, and Sarıdemir., M. (2008). Prediction of mechanical properties of recycled aggregate concretes containing silica fume using artificial neural networks and fuzzy logic. *Comp Mater Sci*, **41**(1),74–82.

[46] Karatas., Ç, Sözen., A, Arcakliogˇlu., E, and Ergüney S. (2007). Modeling of yield length in the mold of commercial plastics using artificial neural networks. *Mater Design*, **28**(1),278–86.

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