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Prediction of 28th Day Compressive Strength of Concrete on the 7th DAY, Using Artificial Neural Network

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Abstract: *Compressive strength of concrete at the age of 28 days is an important parameter for the design of concrete structures, waiting for 28 days to obtain that value is quite time consuming while it is important to ensure the quality control process. In this study an alternative approach using artificial neural network (ANN) model, is proposed to estimate or predict the compressive strength of concrete at 28th day from early age results. In the study concrete cubes of 1:2:4 were cast with different water-cement ratios (0.4, 0.5, 0.6 & 0.65) and their seventh and twenty eighth day strength were measured in the laboratory. In all, 400 cubes of 200 sets of cube crushing test were conducted. ANN model was then developed using the time series tool of ANN in MATLAB 7.12.0 (R2011a) using back propagation algorithm. Out of the 200 sets of results, 110 sets were used for the training of the network while 30 sets were used to validate while 60 sets to test the network. The result of the crushing test shows that the higher the compressive strength at seventh day the higher it will be at twenty eighth day. The result of the ANN model shows a good correlation between the seventh day compressive strength and the twenty eighth day compressive strength with training and validation correlation coefficients of 0.99751 and 0.99736 respectively. It was also found that ANN model is quite efficient in determining the twenty eighth day compressive strength of concrete. The predicted strength values match very well with those obtained experimentally with a correlation coefficient of 0.99675.*

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I. Introduction

1.2 General

Different sciences are developing fast in today's world. In recent decades, man has seen increased relationship of sciences in different fields and the more relationship has led to the appearance of the more new knowledge and technology. Nowadays, one of the most important problems of man is technical and engineering problems (Vahid, 2009). The complexity of most of the problems in this field has made experts of the field use the new mathematical and modeling methods for solving the type of problems. Intelligent systems can be used as suitable tools for identifying complex systems, due to their ability of learning and adaptation (Vahid, 2009).

The main criterion for evaluating the compressive strength of concrete is the strength of the concrete on 28th day. The concrete sample is tested after 28 days and the result of this test is considered as a criterion for quality and rigidity of that concrete (Vahid, 2009). It is well recognized that the prediction of concrete strength is important in the modernized concrete construction and engineering judgment (Dias and Pooliyadda, 2001). Conventional methods of predicting 28-day compressive strength of concrete are basically based upon statistical analysis by which many linear and nonlinear regression equations have been constructed to model such a prediction problem (Monjurul and Ahsanul, 2011).

Obviously, obtaining early strength of concrete takes time, thus results in time delay in forecasting 28-day strength. For many years, researchers have proposed various methods for predicting the compressive strength of concrete. Artificial Neural Network (ANN) has been developed to deal with the problems involving incomplete information. Gunaratnam and Gero, (1994) have used ANN in structural engineering. The study of Neural Networks (NNs) was inspired by biological NNs and was founded by a semi-empirical base to model the behavior of the biological nerve cell structure. The processing elements (neurons) in a NN simulate the function of nerve cells in human brain that contains billions of interconnected neurons. These neurons are the fundamental elements of the central nervous system and determine any action that is taken.

Concrete is a term which cannot be easily defined but beautifully described. It is a heterogeneous mixture produced when a carefully proportion of cement, fine aggregate, coarse aggregate and water are mixed, which hardens to a stone-like mass. Concrete is used more than any man-made material on earth. Mechanical strength is often regarded as the most important property of concrete (Dias and Pooliyadda, 2012). Concrete suffers from one major drawback compared with other materials such as steel and timber; its strength cannot be measured prior to it being poured in a mould. Factors affecting the compressive strength of concrete are water/cement ratio, mix ratio, degree of compaction, type of cement, aggregate grade, design constituent, mixing method, placement, curing method and the presence contaminates (Dias and Pooliyadda, 2012).

A compressive strength of concrete is one of the most important and useful properties of concrete which is determined by testing concrete specimen after curing of 28-days. The compressive strength of concrete is influenced by many factors including mix proportions, curing conditions, water cement ratio and methods of mixing, transporting, placing, vibrations, quality of different ingredients and testing the concrete. Compressive strength is the most important property of concrete because all other properties of concrete depend on a good compressive strength, in other words, as the compressive strength of concrete increases other properties usually improve. The strength of concrete depends on the cohesion of the cement paste, on its adhesion to the aggregate particles and to a certain extent on the strength of the aggregate itself (Gregory, 2005).

Testing of concrete by cubical specimen cannot fully represent the reality of concrete strength on site. The reason for this is that in preparing a specimen, a number of production factors are taken into account. These factors are: deviations from the prescribed proportioning of concrete, varying conditions, loss of moisture in the forms, varying hydro static pressure, the difference in the volume of concrete in specimens and products of many other chance circumstances (Gregory, 2005)

2. Artificial Neural network (ANN)

Artificial neural network (ANN) is a form of artificial intelligence which attempt to mimic the behaviors of the human brain and nervous system. Many authors have described the structure and operation of ANN. A typical structure of ANN consists of a number of processing elements (PEs), or nodes, that are usually arranged in layers: an input layer, an output layer and one or more hidden layers (Fig 1.1). The ANN modeling philosophy is similar to a number of conventional statistical models in the sense that both are attempting to capture the relationship between a historical set of model inputs and corresponding outputs (Shain *et, al*, 2001).

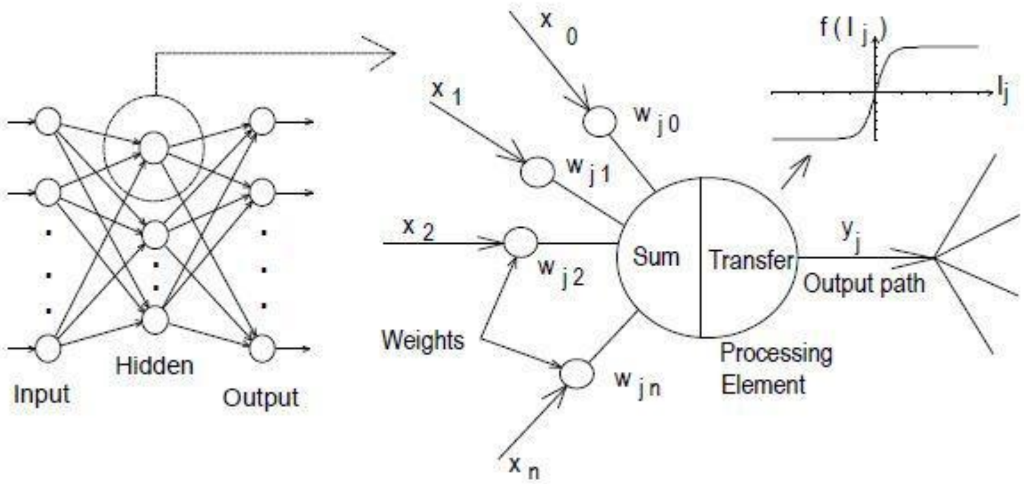

Figure 1; A typical structure of ANN

The input from each PE in the previous layer (x_i) is multiplied by an adjustable connection weight (w_{ji}). At each PE, the weighted input signals are summed and a threshold value (θ_j) is added. This combined input (I_j) is then passed through a non-linear transfer function (f(.)) to produce the output of the PE (y_j). The output of one PE provides the input to the PEs in the next layer. This process is summarized in Equations 1 and 2;

$\sum \boldsymbol{I_j} = \sum \boldsymbol{w_{ji} x_i} + \boldsymbol{\theta_j}$ ……………………………………………………… **1**

Transfer $\boldsymbol{y_j} = \boldsymbol{f(I_j)}$ ……………………………………………………….**2**

The propagation of information in ANNs starts at the input layer where the input data are presented. The network adjusts its weights on the presentation of a training data set and uses a learning rule to find a set of weights that will produce the input/output mapping that has the smallest possible error. This process is called "learning" or "training". Once the training phase of the model has been successfully accomplished, the performance of the trained model has to be validated using an independent testing set. Details of the ANN modeling process and development are beyond the scope of this paper and are given elsewhere (e.g. Moselhi et, al. 199) Artificial Neural Network (ANN) models have been extensively studied with the aim of achieving human-like performance, especially in the field of pattern recognition and system identification. These networks are composed of a number of nonlinear computational elements which operate in parallel and are arranged in a manner reminiscent of biological neural inter-connections. The property that is of primary significance for a neural network is the ability of the network to learn from its environment, and to improve its performance through learning. The improvement in performance takes place over time in accordance with some prescribed measure. A neural network learns about its environment through an interactive process of adjustments applied its synaptic weights and bias levels. Ideally, the network becomes more knowledgeable about its environment after every iteration of the learning process (Simon 1999).

Unlike conventional problem solving algorithms, artificial neural network can be trained to perform a particular task. This is done by presenting the system with a representative set of examples describing the problem, namely pairs of input and output samples. The neural network will then extrapolate the mapping between input and output data. After training, the neural network can be used to recognize data that is similar to any of the examples shown during the training phase (Rafiq M, 2001). The neural network can even recognize incomplete or noisy data, an important feature that is often used for prediction, diagnosis or control purposes. Further, neural networks have the ability to self-organize, therefore enabling segmentation or coarse coding of data. A model is an abstraction that behaves somewhat like a defined ‘‘system’’. In the real world, a system is a set of transformations that convert input states into output states. The key is that it converts input into output through some defined set of algorithms as shown schematically in Figure. 1.1 6

In general, a typical neural network model consists of: (i) an input layer, where input data are presented to the network; (ii) an output layer, which comprises neurons representing target variables; and (iii) one or more hidden intermediate layers. The neural network has a parallel distributed architecture with a large number of nodes and connections with varying weights. Each node has a computation process; multiplying its weight by each input, summation of their product, and then using the activation function to produce the actual output.

The propagation of information in ANN starts at the input layer where the input data are presented. The network adjusts its weights on the presentation of a training data set and uses a learning rule to find a set of weights that will produce the input/output mapping that has the smallest possible error (Jaksa, et, al. 1995). This process is called “learning” or “training”. Once the training phase of the model has been successfully accomplished, the performance of the trained model has to be validated using an independent testing set. ANN learns from data examples presented to them and use these data to adjust their weights in an attempt to capture the relationship between the model input variables and the corresponding outputs (Hecht-Nielsen, 1990). Consequently, ANN doesn’t need any prior knowledge about the nature of the relationship between the input/output variables (Shahin et, al, 2001), which is one of the benefits that ANN have compared with most empirical and statistical methods.

1.3 Mathematical Models for Prediction of 28th Day Compressive Strength

Early prediction of concrete compressive strength enables to know quickly about the concrete and its probable weakness and decide to continue the construction or manage the destruction program. Therefore, prediction of the compressive strength of concrete has been an active area of research. Several methods for early estimation have been introduced in some previously published studies. These attempts were made to predict the 28 days concrete compressive strength from early days test results but those had some limitations (Hamid, et, al 2006).

Many efforts are made on using different techniques as computational modeling, statistical techniques. A number of research efforts have concentrated on using multivariable regression model to improve the accuracy of prediction (Zain, et, al, 2010).

Mathematical model for predicting the compressive strength of the concrete focused on the determination of a general equation of strength gaining nature of concrete with its age (Hasan and Kabir, 2011). Investigation shows that all the concrete strength maintains a correlation with its age according to in Equation (2.12)

$$\boldsymbol{f'_{cD}\frac{D}{D+q}p} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (\mathbf{3})$$

Where f'_{cD} = Strength of the concrete at Dth day (D = 1, 2, 3…); D= Number of days; p and q are constants for each curve but different for different data sets (curves). It may be mentioned this equation (2.12) is similar to equation (2.13) proposed by ACI committee (ACI 209-71) for predicting compressive strength at any day based on 28 days strength. 30

$$\boldsymbol{(f'_c)_t = \frac{t}{a+b.t}(f'_c)_{28d}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots .(\mathbf{4})$$

Here, a and b are constants, $\boldsymbol{(f'_c)_{28d}}$ = 28-day strength and t is the time in days and Equation 2.13 can be recast to similar form of Equation 1. To utilize the derived equation (Equation 2.12), just value of two constants (p and

q) are to be determined. It may be mentioned that the constant q has the unit of day and p has the stress unit to be consistent with the expression.
In Germany, the relation between 28-day strength $f_{c_{28}}$ and the 7-day strength, f_{c_7} is taken to lie between (Shetty 2006),

$$\boldsymbol{f_{c_{28}} = 1.4f_{c_7} + 150} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \textbf{(5)}$$

And

$$\boldsymbol{f_{c_{28}} = 1.7f_{c_7} + 850f_c} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \textbf{(6)}$$

Is being expressed in psi
Where $\boldsymbol{f_c}$ is the compressive strength; A and B are experimental parameters for a given age and x is the water/cement ratio.
Another formula was proposed as follows:

$$f_{c28} = \boldsymbol{K_2(f_{c7})^{K_1}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \textbf{(7)}$$

Where, $\boldsymbol{f_{c7}}$ and f_{c28} are the strengths at 7 and 28 days, respectively. K_1 and K_2 are the coefficients which are varied for different cements and curing conditions. The value of K_1 ranges from 0.3 to 0.8 and that of K_2 from 3 to 6 (Shetty 2006).

II. Materials and Method

The materials used for the research were sourced within Kano and the procedures to arrive at the desired results were carefully followed. The specification and quality of the test materials were kept same throughout the test.
Concrete cubes were cast in 150mm by 150mm by 150mm steel mould at four different water cement ratios 0.4, 0.5, 0.6, 0.65, and then cured in water for 7 days and 28 days respectively. The prepared samples were then tested using compression machine and 7th and 28th day strength was obtained.

2.1 Cement

Ordinary Portland cement (Dangote 3X Cement) manufactured by Dangote Cement Nigeria PLC, was used for the research. The cement is of grade 42.5 and had a specific gravity of 3.14 as determined in accordance with BS 812, (1985).

2.2 Coarse Aggregate

The coarse aggregate used was crushed granite of 20mm maximum nominal diameter and specific gravity of 2.7. Sieve analysis of the coarse aggregate shown in Figure 3.1 was conducted as specified in BS 812 (1985). It was ensured that the aggregates were clean and free from any deleterious material capable of affecting the concrete.

2.3 Fine Aggregate

The fine aggregate used was obtained from river Challawa, Kano state. It was clean and free from any deleterious material that may affect the result.

2.4 Mix Design

The concrete constituents were obtained from the mix ratio of 1:2:4 and water/cement ratio of 0.4, 0.5, 0.6 and 0.65. For each mix proportion, 50 set of cubes were cast. The mix proportion of the concrete is shown in the table below,

Table 1; Showing the compressive strength of the cement material

Cement (kg/m^3)	Fine Aggregate (kg/m^3)	Coarse Aggregate (kg/m^3)	Water (kg/m^3)	W/C
360.4	720.8	1441.7	144.2	0.4
348.8	697.6	1395.2	174.4	0.5
337.6	675.2	1350.4	202.6	0.6
332.2	664.5	1329.0	216.0	0.65

2.5 Compressive Strength

The compressive strengths of the cubes were carried out using the mix proportions in Table 1 for the various mixes. Mixing was done manually and cast in steel cube molds of 150mm and cured in water for 7, and 28 days. A total of 400 cubes amounting to 200 sets were tested and at the end of each curing regime, samples were crushed in accordance with BS12390-3 (2009) using the Avery Denison Compressive Testing machine of 2000 kN load capacity and at constant loading rate of 15kN/s and the average loading rate taken. The summary of results of the compressive strength is shown in Table 2.

Table 2; Relationship of the concrete with respect to water cement ratio

W/C	Cement (kg/m^3)	Fine Aggregate (kg/m^3)	Coarse Aggregate	Coarse aggregate (Kg/m3)	Average Compressive Strength (N/mm^2)	
					7th Day	28th Day
0.4	360.4	720.8	1441.7	1441.7	24.9	38
0.5	348.8	697.6	1395.2	1395.2	20.1	30.5
0.6	337.6	675.2	1350.4	1350.4	16	23.7
0.65	332.2	664.5	1329.0	1329.0	14.3	22.1

The figures (1 and 2) describes an approximately linear relationship between the water-cement ratio and compressive strength, similarly between 7th and the 28th day concrete strength. The 28th day curing concrete increases with increase in the 7th day strength. Their relationship in terms of concrete strength can be defined as the equation below;

$$\boldsymbol{f_{28} = 1.5344 f_7 + 0.3092} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \ (\mathbf{8})$$

where $\boldsymbol{f_{28}}$ = **28th** compressive strength
and $\boldsymbol{f_7}$ = **7th** compressive strength.

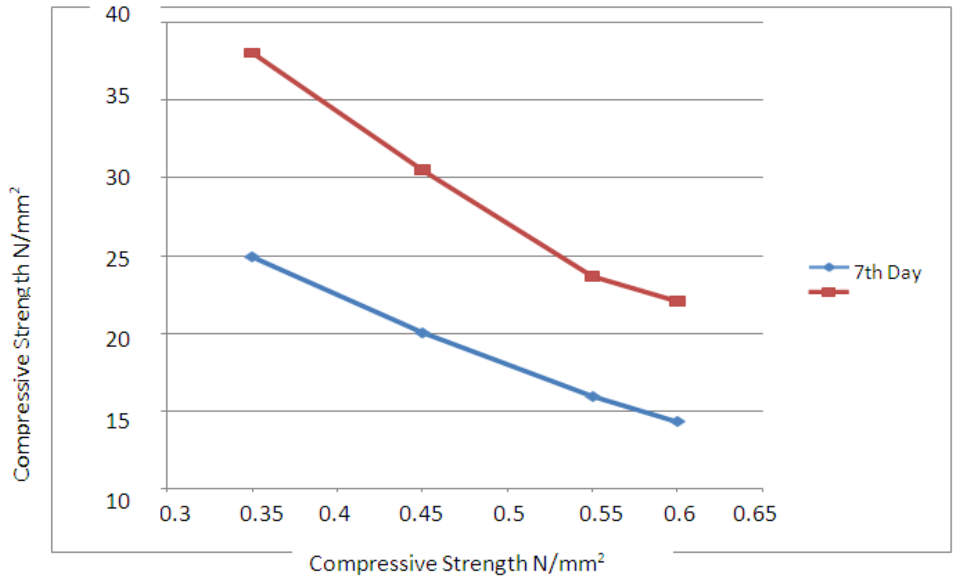

Figure 2; Compressive strength at different water-cement ratio

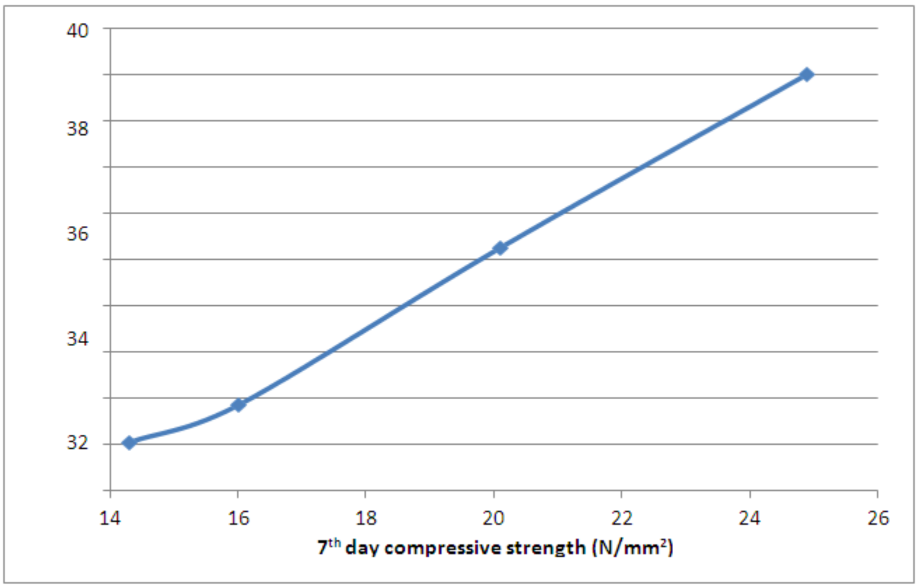

Figure 3; Relationship between the 7th day and 28th day compressive strength

Similarly, table …. Below describes the simple comparison between the results from this experiment and Shetty model.

Table 3; Comparison of experimental and mathematical strength models at 28th day

Experimental Results (N/mm^2)		Shetty Model (N/mm^2)	$f_{28} = 1.5344f_7 + 0.3092$
7th Day	28th Day	28th Day	28th Day
24.9	38	35.89	38.52
20.1	30.5	28.14	31.15
16	23.7	22.4	24.86
14.3	22.1	20.02	22.25

III. Results from the ANN prediction

The results of the network testing and validation shows that the predicted 28th day compressive strength of concrete are very close to those measured in the laboratory. This is an indication that the network has learned the relationship between the input and the output values during the training. The comparison between the measured and predicted compressive strength are shown in the below figures. Overall, the R value for the training dataset was that for the testing set, i.e., the neural network made better prediction for the training data sets than testing datasets. The combination of transfer function composed of tan-sigmoid and linear function gives a good result. Figure 4 & 5 below shows the relationship between output targets and predicted values obtained through the training and testing process. The model shows very good correlation for both the training (R = 0.99751), validation (R = 0.99736) and testing dataset (R = 0.99482) and the general R = 0.99675.

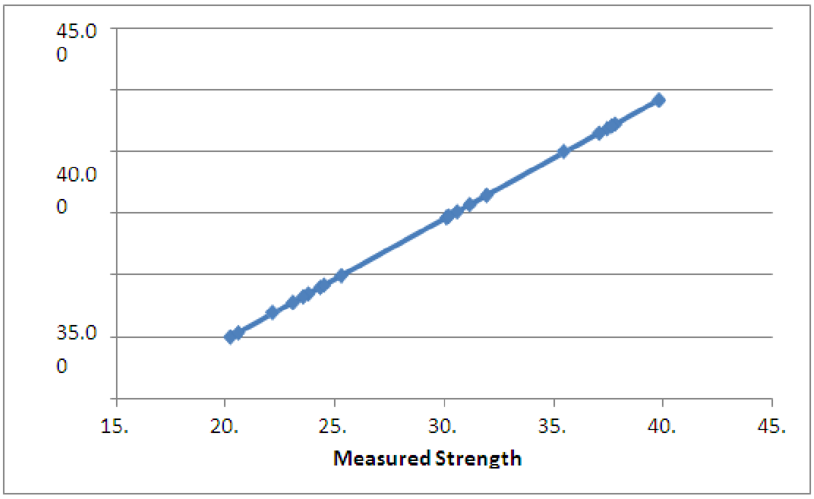

Figure 4; Relationship between measured and predicted 28th daycompressive strength

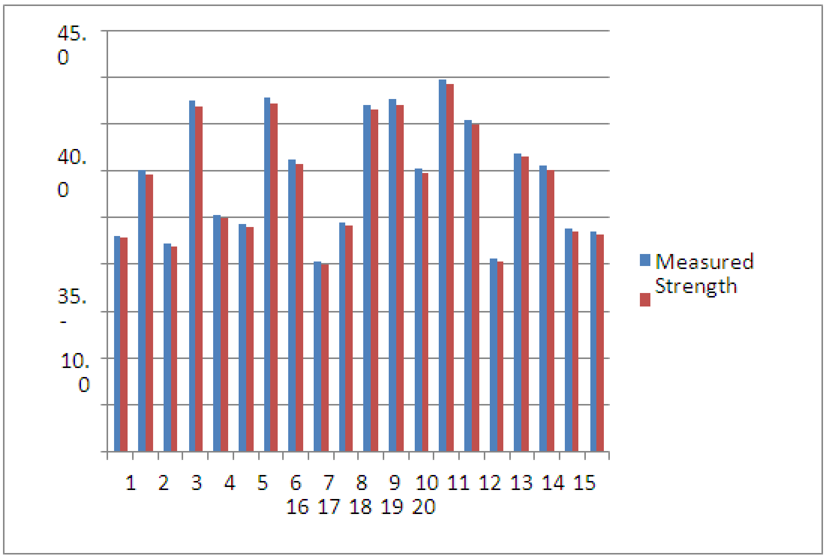

Figure 5; Relationship between measured and predicted 28th day compressive strength

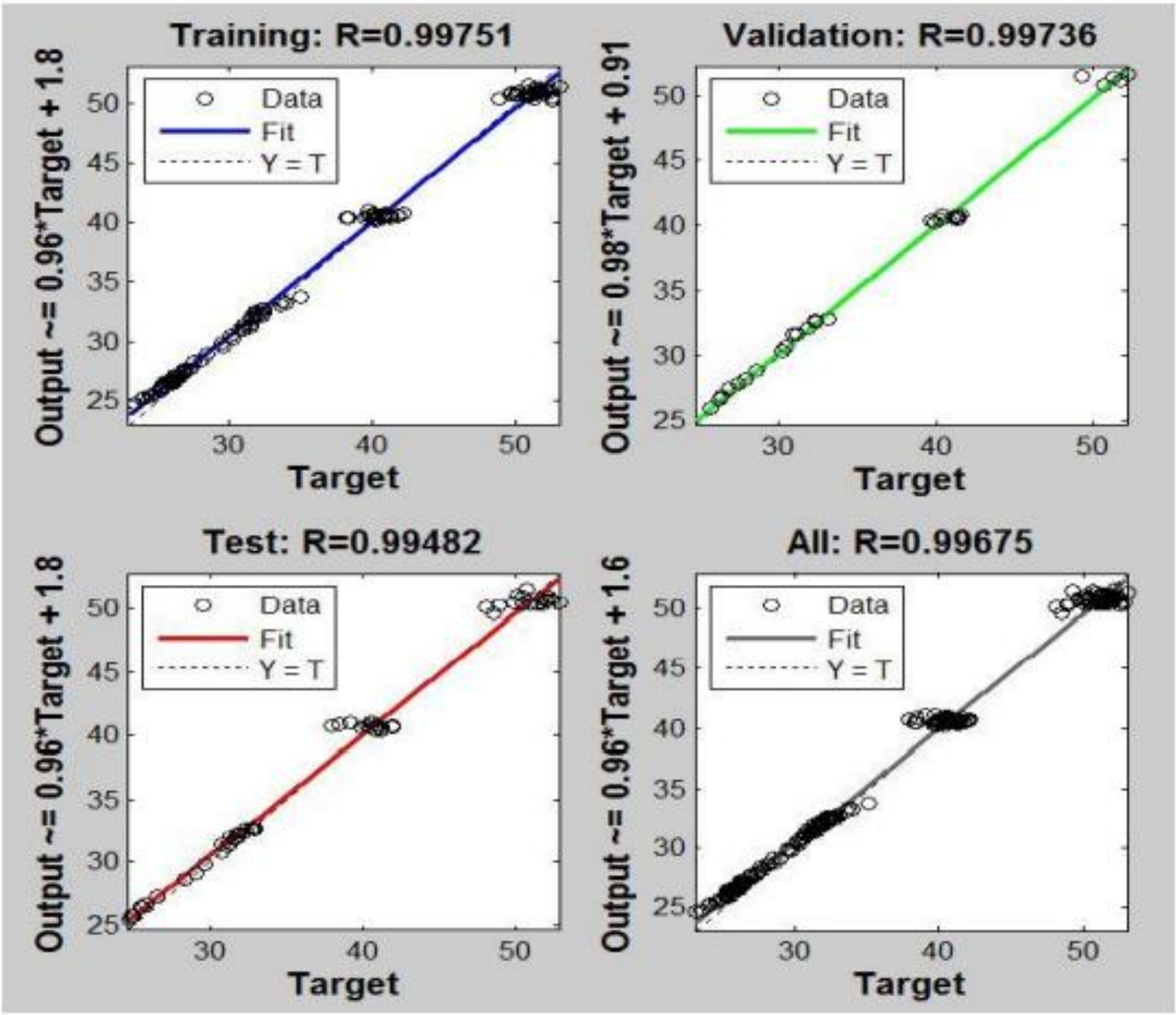

Figure 6; correlation between Measured and ANN Predicted Results

V. Conclusion

The objective of the study was to predict model and correlate the 7th day compressive strength with the 28th day compressive strength. From the study, the following conclusions can be drawn:

1. The 28th day compressive strength was found to be directly proportional to the 7th day compressive strength.
2. Artificial Neural Network toolbox base in commercial software MATLAB (R2011a) was used for the prediction model development. The input layers in this work consist six nodes, one node for each of the independent variables. One hidden layer with ten neurons was developed as the test best network architecture based on the trials and the good regression obtained. The output layer consists of one node representing 28th day strength.
3. From the 200 data sets, 110 randomly collected data were used in the training stage, 30 for validation. After the network had learned the relationship between the input and the output parameters, 60 data sets were used in testing the model. It has been demonstrated in this study that the ANN model is quite efficient in determining the 28th day compressive strength of concrete. It was found that the measured compressive Strength and predicted values are very close with a correlation of 0.99675.
4. Experimental results were slightly higher than mathematical model results

5.1 Recommendations

Based on the findings of this study, artificial neural network is a very good tool for use in the modeling of the relationship between compressive strength at early age and compressive strength at 28th day. Hence, further studies are recommended to cover concrete compositions and conditions.

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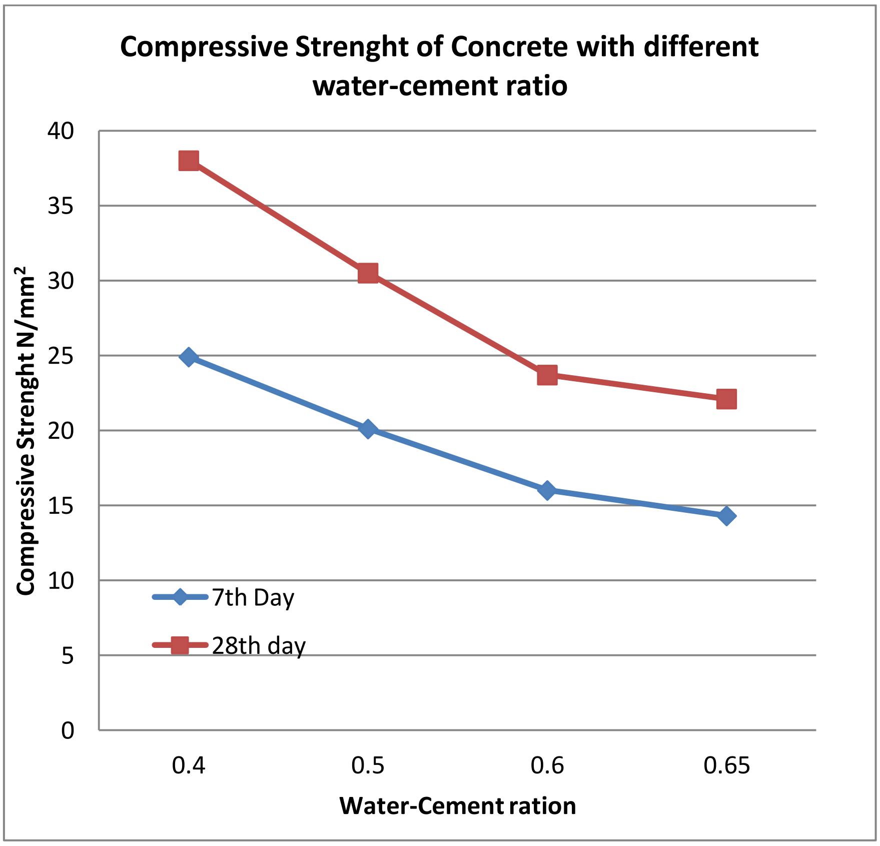
RESULTS AND DISCUSSION



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