PREDICTION OF 28th DAY COMPRESSIVE STRENGTH OF CONCRETE ON THE 7th DAY, USING ARTIFICIAL NEURAL NETWORK

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Declaration

I hereby declare that this work is the product of my research efforts undertaken under the supervision of Dr. A. O. Uche and has not been presented anywhere for the award of a degree or certificate. All sources have been duly acknowledged by means of references.

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Approval Page

This thesis has been examined and approved for the award of Masters in Structural Engineering.

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Dedication

To my Late Mother and Late Grandma, May Allah grants them Jannatul Firdaus, Ameen.

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Notation

ANN Artificial Neural Network

BP Back-propagation

BPNN Back-propagation Neural Network

BS British Standard

EA Difference between the actual and the desired output

EI Rate at which the error changes as the total input received by a unit is changed

EW Error derivative of the weights

f'_c Compressive Strength of Concrete

HPC High-performance concrete

HSC High strength concrete

MART Multiple additive regression tree

NN Neural Network

PEs Processing Elements

W/C Water cement ratio

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 28^{th} 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.

CHAPTER ONE

INTRODUCTION

1.1 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).

1.2 Artificial Neural network (ANN)

Artificial neural network (ANN) is a form of artificial intelligence which attempt to mimic the behaviour 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).

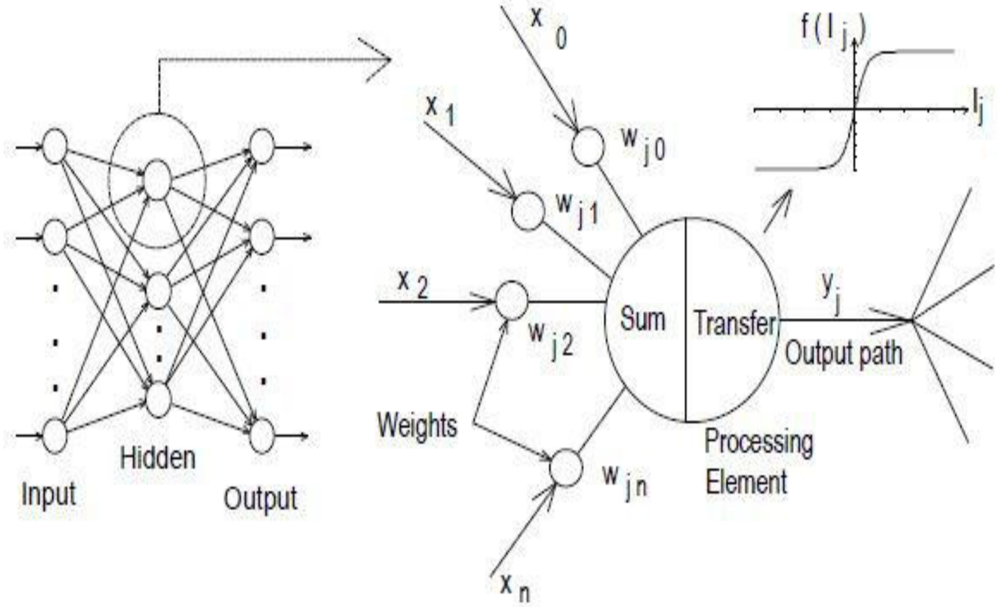


Fig 1.1 A typical structure of ANN

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 1.1 and 1.2

Summation $I_j = \sum w_{ji} x_i + \theta_j$ ……………………………………..1.1

Tranfer $y_j = f(I_j)$ ……………………………………………..….1.2

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

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 Statement of the Problem

Concrete is the most widely used structural material in constructions in the world. Mass concreting in huge civil projects like dams, power plants, bridges, etc., usually is not practicable and it is necessary to be performed in several layers and the compressive strength of each layer should not be less than the specified compressive strength. Therefore, one has to wait 28 days to achieve 28-day strength of each layer of concrete. Therefore if we have *n* layers of concrete we need $28\times n$ days to complete the total project (Alilou, 2009). The aforementioned reason necessitated the need to investigate the feasibility of using the ANN in predicting the 28-day compressive strength using the 7-day compressive strength in order to eliminate the waiting period.

1.4 Justification of Study

The current study was performed to experimentally predict the strength of concrete having known the strength at the seventh day. The purpose of this work is to investigate the ability of an ANN to predict the 28 day compressive strength of concrete. The performance of the ANN model is compared with experimental data and other published analytical models. The study is based on laboratory test specimens.

1.5 Aim and objectives

1.5.1 Aim

The aim of the research is to predict the 28th day compressive strength of concrete on the seventh day using artificial neural network.

1.5.2 Objectives

i. To determine experimentally the compressive strength of concrete at 7th and 28th days

ii. To train a model that can predict the 28th day compressive strength having determined its seventh day.

iii. To validate the model and test the model

1.6 Scope and Limitation

1.6.1 Scope

The artificial neural network will be developed using the ANN tool box based in MATLAB (R2011a) software to predict the 28^{th} day compressive strength of concrete.

1.6.2 Limitation

Concrete mix will be limited to 1:2:4 mix ratios, at 0.4, 0.5, 0.6 & 0.65 water – cement ratio.

1.7 Significance of the study

In addition to quality assurance and control this study will go a long way improving the delivery time and cost of construction projects

CHAPTER TWO

LITERATURE REVIEW

2.1 Concrete

Concrete is an artificial stone which is obtained after hardening the heterogeneous mixtures of cement, water, aggregates and sometimes admixture and/or additive (to modify the fresh and hardened concrete property). The concrete composition must be established in order to assure the resistance and durability of building elements, by using less cement content. (Catalin and Liana, 2008)

2.1.1 Cement

Cement is a material that has adhesive and cohesive properties enabling it to bond mineral fragments into a solid mass. Cement consists of silicates and aluminates of lime made from limestone and clay (or shale) which is ground, blended, fused in a kiln and crushed to a powder. Cement chemically combines with water (hydration) to form a hardened mass.

Typical portland cements are mixtures of tricalcium silicate (3CaO • SiO2), tricalcium aluminate (3CaO • Al2O3), and dicalcium silicate (2CaO • SiO2), in varying proportions, together with small amounts of magnesium and iron compounds. Gypsum is often added to slow the hardening process. (Wang and Charles, 2010)

Portland cement is made by blending the appropriate mixture of limestone and clay or shale together and by heating them at $1450^{o}C$ in a rotary kiln. The preliminary steps are a variety of blending and crushing operations. The raw feed must have a uniform composition and be a size fine enough so that reactions among the components can complete in the kiln. Subsequently, the burned clinker is ground with gypsum to form the familiar grey powder known as Portland cement.

2.1.2 Water

The water has two roles in concrete mixture, the chemical with cement and perform cement hydration and second is to make the concrete composition fluent and workable. The water which is used to make the concrete is clean water. The impurity in water can have undesirable effect on concrete strength. (Teshnehlab and Alilou, 2010)

The setting and hardening of concrete are the result of chemical and physical processes that take place between Portland cement and water, i.e. hydration. To understand the properties and behaviour of cement and concrete some knowledge of the chemistry of hydration is necessary.

2.1.3 Aggregate

Since aggregate usually occupies about 75% of the total volume of concrete, its properties have a definite influence on behaviour of hardened concrete. Not only does the strength of the aggregate affect the strength of the concrete, its properties also greatly affect durability (resistance to deterioration under freeze-thaw cycles). Since aggregate is less expensive than cement it is logical to try to use the largest percentage feasible. Hence aggregates are usually graded by size and a proper mix has specified percentages of both fine and coarse aggregates. Fine aggregate (sand) is any material passing through a No. 4 sieve of BS 410, (1986). Coarse aggregate (gravel) is any material of larger size.

Fine aggregate provides the fineness and cohesion of concrete. It is important that fine aggregate should not contain clay or any chemical pollution. Also, fine aggregate has the role of space filling between coarse aggregates. Coarse aggregate includes: fine gravel, gravel and coarse gravel In fact coarse aggregate comprises the strongest part of the concrete. It also has reverse effect on the concrete fineness. The more coarse aggregate, the higher is the density and the lower is the fineness. (Wang and Charles, 2010)

2.1.4 Water – Cement Ratio

The water–cement ratio is the ratio of the weight of water to the weight of cement used in a concrete mix and has an important influence on the quality of concrete produced. A lower water-cement ratio leads to higher strength and durability, but may make the mix more difficult to place. Placement difficulties can be resolved by using plasticizers or super-plasticizers.

Concrete hardens as a result of the chemical reaction between cement and water (known as hydration, this produces heat and is called the heat of hydration). For every pound (or kilogram or any unit of weight) of cement, about 0.25 pounds of BS 410, (1986) (or 0.25 kg or corresponding unit) of water is needed to fully complete the hydration reactions. This requires a water-cement ratio of 1:4 often given as a proportion: 0.25. However, a mix with a w/c ratio of 0.25 may not mix thoroughly, and may not flow well enough to be placed, so more water is used than is technically necessary to react with the cement. More typical water-cement ratios of 0.4 to 0.6 are used. For higher-strength concrete, lower water: cement ratios are used, along with a plasticizer to increase flow ability (Jurash, 2013).

Too much water will result in segregation of the sand and aggregate components from the cement paste. Also, water that is not consumed by the hydration reaction may leave the concrete as it hardens, resulting in microscopic pores (bleeding) that will reduce the final strength of the concrete. A mix with too much water will experience more shrinkage as the excess water leaves, resulting in internal cracks and visible fractures (particularly around inside corners) which again will reduce the final strength (Wang and Charles, 2010).

2.2 Compressive Strength of Concrete

The strength of concrete is controlled by the proportioning of cement, coarse and fine aggregates, water, and various admixtures. The ratio of the water to cement is the chief factor for determining concrete strength as shown in Figure 2.1. The lower the water-cement ratio, the higher is the compressive strength. A certain minimum amount of water is necessary for the proper chemical action in the hardening of concrete; extra water increases the workability (how easily the concrete will flow) but reduces strength. A measure of the workability is obtained by a slump test. Actual strength of concrete in place in the structure is also greatly affected by quality control procedures for placement and inspection. The strength of concrete is denoted in the United States by $f'c$ which is the compressive strength of test cylinder measuring 6 in. in diameter by 12 in. high measured on the 28th day after they are made.

Strength is the design property of the concrete. Characteristics like, durability, permeability, volume stability may be important in some case of designing concrete structure but strength is the most important one. An overall picture of concrete quality is being reflected by the concrete strength. The process of strength growth is called 'hardening'. This is often confused with 'setting' while setting and hardening are not the same. Setting is the stiffening of the concrete from its fluid state after it has been placed. On the other hand hardening is the process of strength growth and may continue for weeks or months after the concrete has been mixed and placed. The rate at which concrete sets is independent of the rate at which it hardens. There are many factors which control concrete compressive strength. Concrete mix proportioning, aggregate quality, aggregate gradation, type of cement, mixing and placing method, concrete curing and curing temperature and the most important one is the water cement ratio. Water cement (W/C) ratio has a critical impact on concrete strength characteristic. A minimum amount of water is necessary for proper chemical reaction in the concrete and extra amount of water increases the workability and reduces strength (Gregory, 2005).

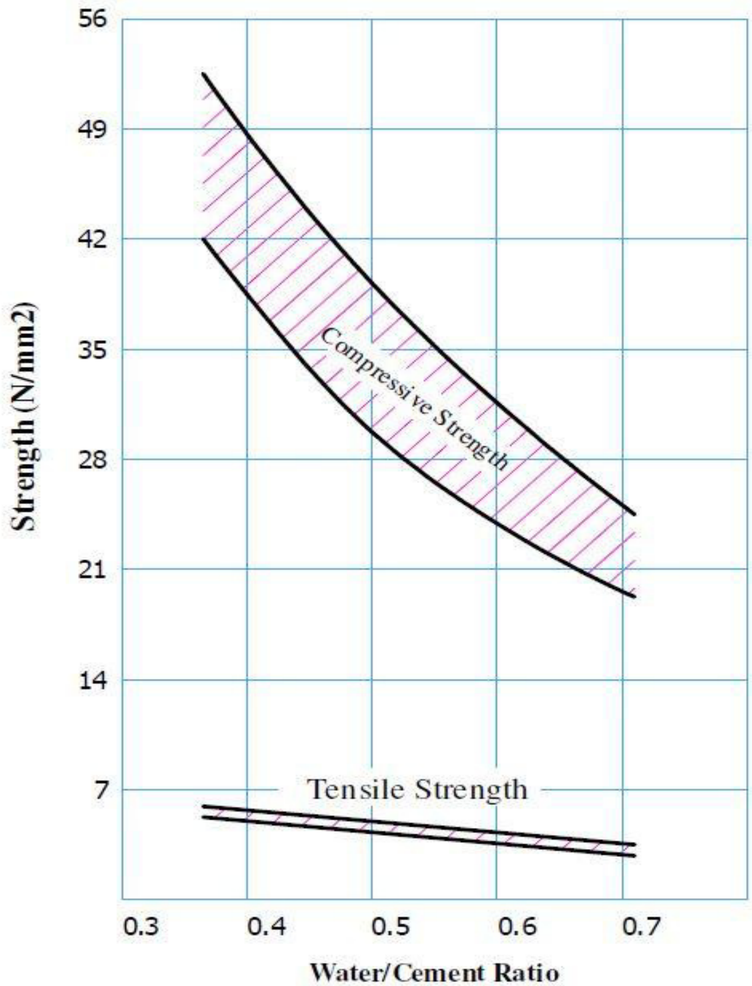


Figure 2.1: Relationship between water-cement ratio and compressive strength of concrete

There are lots of parameters effects on compressive strength of concrete. But the most important parameters were presented in Table 2.1.

Table 2.1: Parameters that affect the Compressive Strength of Concrete

Row	Parameter	Unit	Range
1	Mix Design	-	A-L
2	Water/Cement Ratio	%	35.0 - 75.0
3	Density	ton/m3	2.30 - 2.60
4	Slump	mm	70 - 150
5	Air	%	1.0 - 7.0
6	Silica fumes	gr	0 - 400
7	Super-Plasticizer	kg	0.0 - 3.5
8	Age	day	3, 7, 14, 28, 42
9	Compressive Strength	kg/cm2	70.00 - 420.00

(Vahid and Mohammad, 2011)

The 1st to 7th parameters presented in Table 2.1 are determined in the first day. There is a salient point about 8th parameter (age). As previously mentioned, the concrete age has a direct arithmetic relation with the concrete strength. The more aged the concrete the higher is the compressive strength (Alilou 2009).

Here is an interesting point so that the 3-day compressive strength of concrete has a mathematical relation with the compressive strength of the same concrete in 7th, 14th, 28th and 42th day. Therefore, it can be used as an important parameter for prediction of this system. In other words, the 3-day compressive strength of concrete is a very good criterion to achieve the 28-day compressive strength (Alilou and Teshnehlab 2009).

It is conceived from Figure 2.2 that the higher the 3-day compressive strength the higher is the 28- day compressive strength of the concrete. Figure 2.2 shows the relationship between 3-day compressive strength and

28-day compressive strength for 4 types of concrete with variable w/c ratios, this relation is linear relatively (Alilou and Teshnehlab 2009).

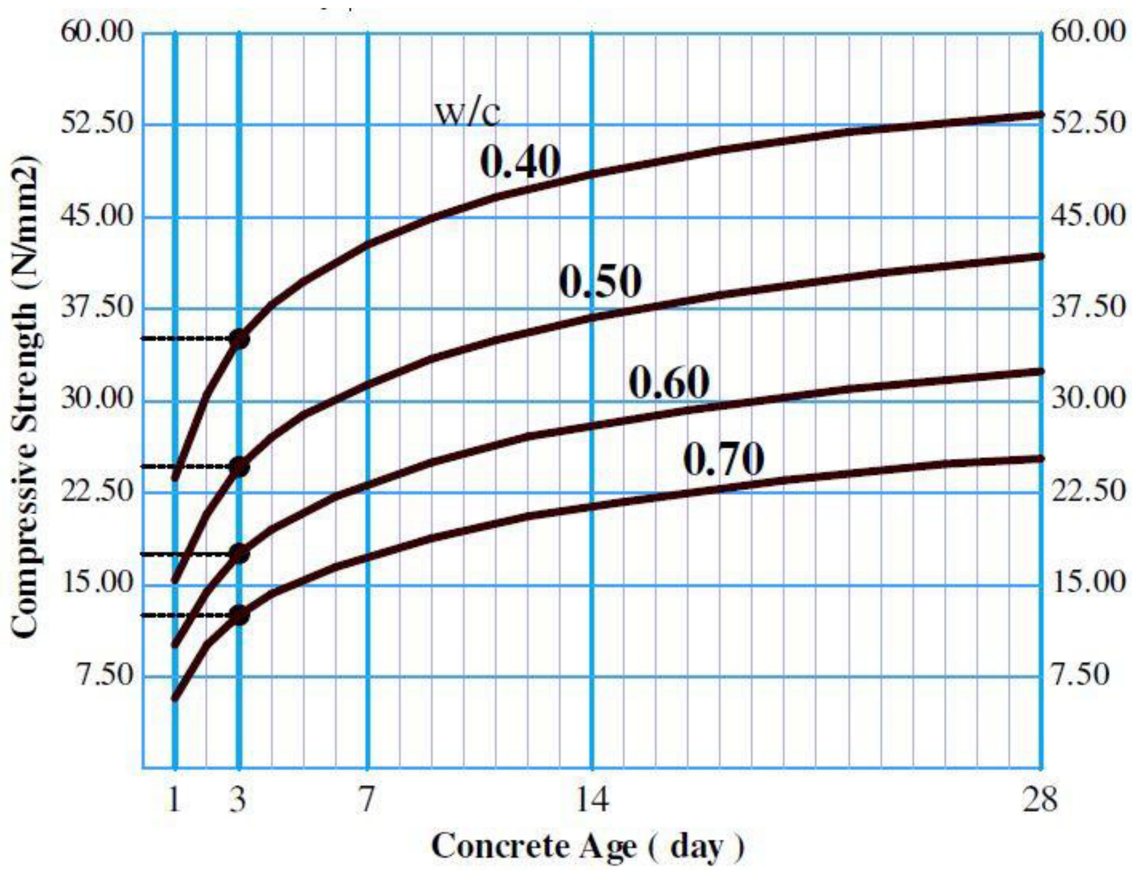


Figure 2.2 Relationship between Concrete Age, Water-cement Ratio and Compressive Strength (Vahid and Mohammad, 2011)

2.3 Artificial Neural Network

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).

Kasperkiewicz et, al., (1995) used artificial neural network of the Fuzzy-ARTMAP type for predicting strength properties of high-performance concrete (HPC) mixes. The 28-days compressive strength was considered the only intended for the prediction. A significant correlation between the actual strength and the predicted value by the neural network was observed. Results obtained suggested that the problem of prediction of concrete properties can be effectively modelled in a neural system, in spite of incomplete data.

Yaqub et, al (2006) gave mix design developed for high strength concrete with locally available constituents of concrete selected for the purpose of determining their relative quantities and proportions for the best outcome. Four mixes were used to achieve a compressive strength up to 162 Mpa. The variables were aggregate sizes and mix ratio. Four mix ratios by weight were selected with 0.30 water cement ratio in addition to this ultra727 super plasticizer was used to improve the workability of concrete mix. It was observed that the compressive strength depends on mix proportions, size and texture of aggregates and method of compaction. Yeh, (2006) found that fly ash and slag concrete is a highly complex material whose behaviour is difficult to model and described a method of modelling slump of fly ash and slag concrete using artificial neural networks. The model built was examined with response trace plots to explore the slump behaviour of fly ash and slag concrete. Author brings to a close conclusion that response trace plots can be used to explore the complex nonlinear relationship between concrete components and concrete slump.

Noorzaei et, al (2007) focused on development of artificial neural networks (ANN) for prediction of compressive strength of concrete after 28 days. To predict the compressive strength of concrete six input parameters cement, water, silica fume, super plasticizer, fine aggregate and coarse aggregate were identified considering two hidden layers for the architecture of neural network. The performance of the 6-12-6-1 architecture was observed to be the best possible architecture. The results of the study indicated that ANN has strong potential as a feasible tool for predicting the compressive strength of concrete. Mohammad et, al. (2009) reported the importance of the ingredient materials for producing high strength concrete (HSC) along with the results of an experimental study on achieving high strength concrete. Chou et, al (2011) optimized the prediction accuracy of the compressive strength of high-performance concrete (HPC) by comparing data-mining methods. The compressive strength of high performance concrete is observed to be a function of all concrete content, including cement, fly ash, and blast furnace slag, water, super plasticizer, age, and coarse and fine aggregate. The quantitative analyses in this study were performed by using five different data-mining methods i.e. artificial neural network, support vector machines, multiple regression, multiple additive regression trees and bagging regression trees. The methods were developed and tested against a data set derived from 17 concrete strength test laboratories.

The cross-validation of unbiased estimates of the prediction models for performance comparison purposes indicated that multiple additive regression tree (MART) was superior in prediction accuracy, training time, and aversion to over fitting. Analytical results also suggested that MART-based modelling is effective for predicting the compressive strength of varying HPC age. Barbuta et, al (2012) concludes the study conducted with neural networks for determining the properties of polymer concrete with fly ash. In the study polymer concrete with different contents of fly ash and resin was prepared and tested for determining the influence of fly ash on the properties. Using neural networks, the experimental results were analysed for predicting the compressive strength and flexural strength and also on the basis of a model with given values of properties to ascertain the composition. This motivates the authors to use artificial neural network with two different training algorithms of standard error back propagation and Jordan- Elman type in the neural architecture. The next section describes the research objectives and methodology adopted in this paper.

2.3.1 The Concept of Artificial Neural Network

Much is still unknown about how the brain trains itself to process information, so theories abound. In the human brain, a typical neuron collects signals from others through a host of fine structures called dendrites. The neuron sends out spikes of electrical activity through a long, thin stand known as an axon, which splits into thousands of branches. At the end of each branch, a structure called a synapse converts the activity from the axon into electrical effects that inhibit or excite activity from the axon into electrical effects that inhibit or excite activity in the connected neurones. When a neuron receives excitatory input that is sufficiently large compared with its inhibitory input, it sends a spike of electrical activity down its axon. Learning occurs by changing the effectiveness of the synapses so that the influence of one neuron on another changes (Park, 2011).

These neural networks were conducted by first trying to deduce the essential features of neurones and their interconnections. Then typically program a computer to simulate these features. However because our knowledge of neurones is incomplete and our computing power is limited, our models are necessarily gross idealisations of real networks of neurones.

Artificial neural networks are typically composed of interconnected "units", which serve as model neurons. The function of the synapse is modeled by a modifiable weight, which is associated with each connection. Each unit converts the pattern of incoming activities that it receives into a single outgoing activity that it broadcasts to other units. It performs this conversion in two stages:

I. It multiplies each incoming activity by the weight on the connection and adds together all these weighted inputs to get a quantity called the total input.

II. A unit uses an input-output function that transforms the total input into the outgoing activity.

2.3.2 The Mathematical Modelling of Artificial Neuron

A neuron is an information processing unit that is fundamental to the operation of a neural network. As shown in Figure 2.3, according to Park (2011), there are three basic elements of the neuron model may be identified. A set of synapses or connecting links (indicated by j), that may receive a signal x_j, each of which is characterized by a weight wkj. It is important to make a note of the manner in which the subscripts to the synaptic weight wkj are written as suggested by Demuth et, al (2006). The first subscript refers to the neuron in question and the second subscript refers to the input end of the synapse to which the weight refers. The weight wkj positive if the associated synapse is excitatory; it is negative if the synapse is inhibitory. An adder for summing up the input signals, weighted by respective synapses of the neuron. An activation function that limits (the amplitude of) the output of a neuron, The activation function is also referred to in the literature as a squashing in that it squashes (limits) the permissible amplitude range of the output signal to some finite value.

Typically, the normalized amplitude range of the output of a neuron is written as the closed unit interval [0, 1] or alternately [-1, 1]. The model of a neuron also includes an externally applied bias (threshold) wk_o = bk that has the effect of lowering or increasing the net input of the activation function.

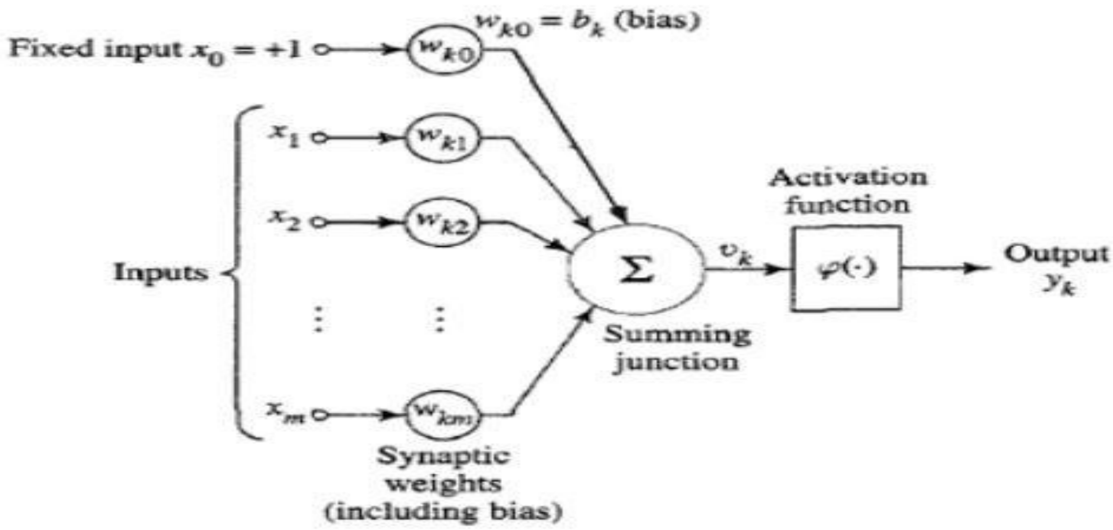


Figure 2.3: Basic element of an artificial neuron (source: Park, 2011)

2.3.3 Activation Function

An activation function performs a mathematical operation on the output. More sophisticated activation functions can be utilized depending upon the type of problem to be solved by the network. A linear function satisfies the superposition concept. The function is shown in Figure 2.4(a). The mathematical equation for the above linear function can be written as

$$Y = f(u) = \alpha . u \text{ --(2.1)}$$

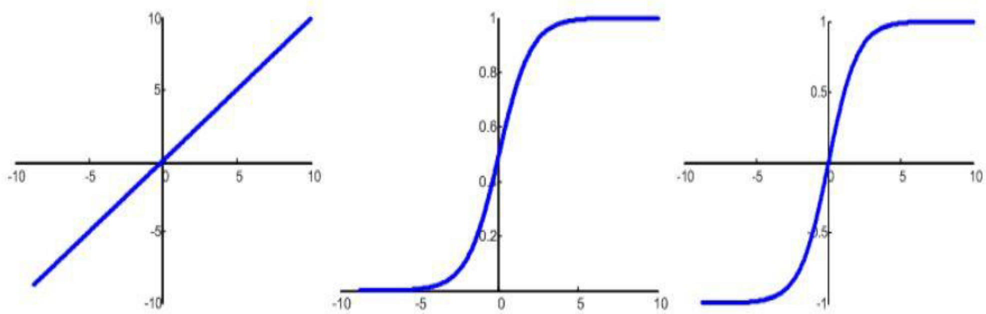
Where α is the slope of the linear function. If the slope α is 1, the linear activation is called the identity function. The output (y) of identity function is equal to input function (u). Although this function might appear to be a trivial case, nevertheless it is very useful in some cases such as in Figure 2.4; sigmoid (S shape) function is the most common nonlinear type of the activation used to construct the neural networks. It is mathematically well behaved, differentiable and strictly increasing function. A sigmoidal transfer function can be written in the following form.

$$f(x) = \frac{1}{1+e^{-\alpha x}} \ , \quad 0 \le f(x) \le 1 \text{ ------------------------(2.2)}$$

where α is the shape of the sigmoid function. By varying this parameter, different shapes of the function can be obtained as illustrated in Figure 2.4(b). this function is continuous and differentiable.

Tangent sigmoidal function is described by the following mathematical form:

$$f(x) = \frac{2}{1+e^{-\alpha x}} - 1 \ , \quad -1 \le f(x) \le +1 \text{ ----------------------(2.3)}$$



(a) (b) (c)

Figure 2.4: Activation Function

2.3.4 Multilayered Neural Network

The source nodes in input layer of the network supply respective element of the activation pattern (input vector). Which constitute the input signals applied to the neurons (computation nodes) in the second layer (i.e. the first hidden layer). The output signal of the second layer are used as inputs to the third layer, and so on for the rest of the network. Typically, the neuron in each layer of the network has as their input the output signals of the preceding layer only. The set of output signal of the neuron in the output layer of the network constitute the overall response of the network to the activation pattern supplied by the source nodes in the input layer (Najjar and Ali, 1999). The commonest type of artificial neural network consists of three groups, or layers, of units: a layer of "input" units is connected to a layer of "hidden" units, which is connected to a layer of "output" units. (see Figure 2.5) The activity of the input units represents the raw information that is fed into the network. The activity of each hidden unit is determined by the activities of the input units and the weights on the connections between the input and the hidden units. The behaviour of the output units depends on the activity of the hidden units and the weights between the hidden and output units.

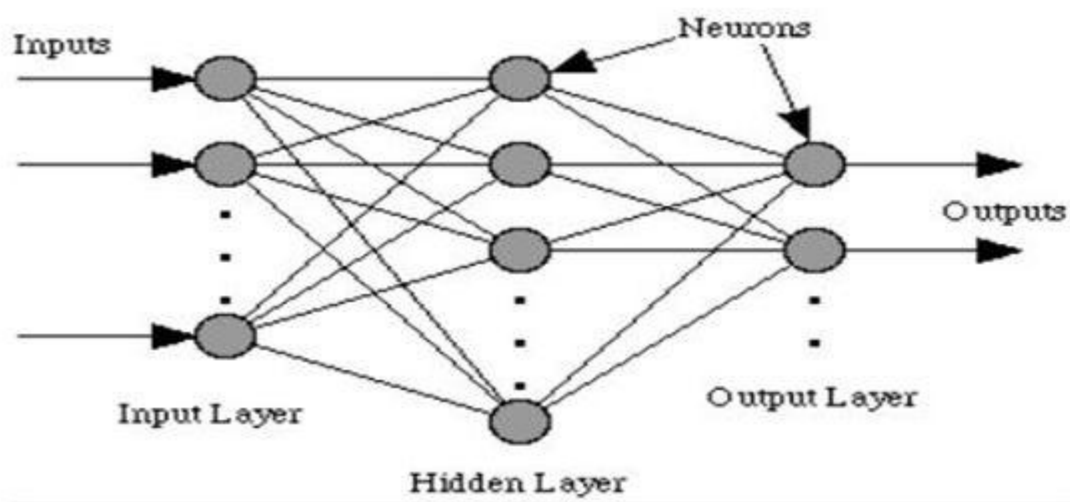


Figure 2.5: Example of Multilayer Neural Network

2.3.4 Back-propagation

Back-propagation Neural Network (BPNN) algorithm is one of the most widely used and a popular technique to optimize the feed forward neural network training. Traditional BP (Back-propagation) algorithm has some drawbacks, such as getting stuck easily in local minima and slow speed of convergence. Nature inspired meta-heuristic algorithms provide derivative-free solution to optimize complex problems. The purpose of BP training is to change iteratively the weights between the neurons in a direction that minimizes the error E, defined as the squared difference between the desired and the actual outcomes of the output nodes, summed over training patterns (training dataset) and the output neurons.

To train a neural network to perform some task, we must adjust the weights of each unit in such a way that the error between the desired output and the actual output is reduced. This process requires that the neural network compute the error derivative of the weights (EW). In other words, it must calculate how the error changes as each weight is increased or decreased slightly. The back propagation algorithm is the most widely used method for determining the EW. The back-propagation algorithm is easiest to understand if all the units in the network are linear. The algorithm computes each EW by first computing the EA, the rate at which the error changes as the activity level of a unit is changed. For output units, the EA is simply the difference between the actual and the desired output. To compute the EA for a hidden unit in the layer just before the output layer, we first identify all the weights between that hidden unit and the output units to which it is connected. We then multiply those weights by the EAs of those output units and add the products. This sum equals the EA for the chosen hidden unit. After calculating all the EAs in the hidden layer just before the output layer, we can compute in like fashion the EAs for other layers, moving from layer to layer in a direction opposite to the way activities propagate through the network. This is what gives back propagation its name. Once the EA has been computed for a unit, it is straight forward to compute the EW for each incoming connection of the unit. The EW is the product of the EA and the activity through the incoming connection.

For non-linear units, the back-propagation algorithm includes an extra step. Before back-propagating, the EA must be converted into the EI, the rate at which the error changes as the total input received by a unit is changed.

2.3.6 Designing the structure of Artificial Neural Network

Structural design of NN involves the determination of layers and neurons in each layer and selection of training algorithm. The selection of only effective input parameters to the NN is one of the most difficult processes since: (1) there may be interdependencies and redundancies between parameters, (2) sometimes it is better to omit some parameters to reduce the total number of input parameters, and therefore computational complexity of the problem and topology of the network, and (3) NN is usually applied to problems where there is no strong knowledge about the relations between input and output, and therefore it is not clear which of the input parameters are most useful. Moreover, other design parameters of NN architecture, such as the number of neurons in input layer, number of hidden layers, number of neurons in hidden layers and number of neurons in output layer, are found using several repeated runs of the system based on trial and error method. There is no clear framework to select the optimum NN architecture and its parameters (Chung and Kusiak, 1994; Kusiak and Lee, 1996). Nevertheless, some research work has contributed to determine the number of hidden layers, the number of neurons in each layer, selecting the learning rate parameter, and others.

2.3.7 Determining the Number of Hidden layers

Determining the number of hidden layers and the number of neurons in each hidden layer is a considerable task. The number of hidden layers is usually determined first and is a critical step. The number of hidden layers required depends on the complexity of the relationship between the input parameters and the output value. Most problems only require one hidden layer, and if relationship between the inputs and output is linear the network does not need a additional hidden layer at all. It is unlikely that any practical problem will require more than two hidden layers (THL).

Cybenko (1989) and Bounds et, al., (1988) suggested that one hidden layer (OHL) is enough to classify input patterns into different group. Chester (1990) argued that a THL should perform better than an OHL network. More than one hidden layer can be useful in certain architectures, such as cascade correlation (Fahlman and Lebiere, 1990) and others. A simple explanation for why larger networks can sometimes provide improved training and lower generalization error is that the extra degrees of freedom can aid convergence; that is, the addition of extra parameters can decrease the chance of becoming stuck in local minima or on "plateaus". The most commonly used training methods for back-propagation networks are based on gradient descent; that is, error is reduced until a minimum is reached, whether it is a global or local minimum. However, there isn't clear theory to tell how many hidden units are needed to approximate any given function. If only one input available, one sees no advantages in using more than one hidden layer. But things get much more complicated when two or more inputs are given. The rule of thumb in deciding the number of hidden layers is normally to start with OHL (Lawrence, 1994). If OHL does not train well, then try to increase the number of neurons. Adding more hidden layers should be the last option.

2.3.8 Determining the number of hidden neuron

The choice of hidden neuron size is problem-dependent. For example, any network that requires data compression must have a hidden layer smaller than the input layer (Swingler, 1996). A conservative approach is to select a number between the number of input neurons and the number of output neurons. It can be seen that the general wisdom concerning selection of initial number of hidden neurons is somewhat conflicting. A good rule of thumb is to start with the number of hidden neurons equal to half of the number of input neurons and then either add neurons if the training error remains above the training error tolerance, or reduce neurons if the training error quickly drops to the training error tolerance. Table 2.2 give the rule of thumbs to select the number of neurons in hidden layer

Table 2.2: Rule of thumbs to select the number of neurons in hidden layer

Formula	**Comments**
h=2i +1	Hecht-Nelson (1987) used Kolmogorov's which any function of I variables may be represented by the superposition of set of 2i+1 univarite function-to derive the upper bound for the required number of hidden neurons
h=(I + o)/2 $\frac{N}{10} - i - o \leq h \leq \frac{N}{2} - i - o$	Lawrence and Frederickson (1988) suggested that a best estimation for the number of hidden neurons is to half the sum of inputs and outputs. Moreover, they proposed the range of hidden neurons.
h=ilog$_2$P	Marchandani and Cao (1987) proposed a number an equation for best number of hidden neurons

(Sourced: Park, 2011)

Where, h = the number of hidden neurons, I = the number of input neurons, o = number of output

2.3.9 Determining the number of training data

In order to train the neural network well, the number of data set must be carefully decided. An over fitted model could approximate the training data well but generalize poorly to the validation data set. On the other hand, an under fitted model would generalize to the validation data set well but approximate the training data poorly. To avoid over fitting and under fitting is to determine the best number of training observations. No general guidelines are available to achieve this. However, Lawrence and Fredrickson (1988) suggested the following rule of thumb as in equation: 2.6

$2 (I + H + O) \leq N \leq 10((I + H + O)$ -------------------------- (2.6)

Where:

I = number of neuron in the input layer

H = number of neuron in the hidden layer

O = number of neuron in the output layer

2.3.10 Mathematical Formulation

Training a neural network is conducted by presenting a series of example patterns for associated input and output values. Initially, when a network is created, the connection weights and biases are set to random values. The performance of an ANN model is measured in terms of an error criterion between the target output and the calculated output.

The output calculated at the end of each feed-forward computation is compared with the target output to estimate the mean-squared error, as shown in Equation (`2.7)

$$E = \sum_{i=1}^{Num}(T_i - t_i)^2 \quad \text{---------------------------- (2.7)}$$

Where, Num = number of target data, Ti = ith target output, ti = ith calculated output, respectively.

An algorithm called back-propagation is then used to adjust the weights and biases until the mean-squared error is minimized. The network is trained by repeating this process several times. Once the ANN is trained, the prediction mode simply consists of propagating the data through the network, giving immediate results. In this study, the training data sets (inputs and target outputs) were normalized according to Equation (2.8). Processing of the training data was performed so that the processed data were in the range of -1 to +1. The output of the network was trained to produce outputs in the range of -1 to +1, and we converted these outputs back into the same units used for the original targets.

$pn = 2 (p - \min p) / (\max p - \min p) - 1$, $tn = 2 (t - \min t) / (\max t - \min t) - 1$ -- (2.8)

Where p = a matrix of input vectors; t = a matrix of target output vectors; pn = a matrix of normalized input vectors; tn = a matrix of normalized target output vectors; max p = a vector containing the maximum values of the original input; min p = a vector containing the minimum value of the original input; max t = a vector containing the maximum value of the target output; and min t = a vector containing the minimum value of the target output. The normalized data were then used to train the neural network to obtain the final connection weights. The data from the output neuron have to be post-processed to convert it back into non-normalized units as shown in Equation (2.9).

$t = 0.5\ \alpha\ (tn + 1)\ \alpha\ (\max t - \min t) + \min t$ ---------------------------- (2.9)

The normalized output is then obtained by propagating the normalized input vector through the network as in Equation (2.10)

$tn = W2 \times \log \mathit{sig}\ (W1 \times pn + B1) + B2$ --------------------------- (2.10)

Where:

W1 = a weight matrix representing connection weights between the input layer neurons and the hidden layer;

B1 = a weight matrix representing connection weights between the hidden layer neurons and the output neuron;

W2 = a bias vector for the hidden layer neurons; and

B2 = a bias for the output neuron.

The log-sigmoid function log sig is defined in Equation (2.11). The output t is then obtained using Equation (2.9) and (2.10) respectively.

$t = 0.5\ \alpha\ (W2 \times \log sig\ (W1 \times pn + B1) + B2 + 1)\ \beta\ (\max t - \min t) + \min t$ --- (2.11)

Where the transfer function in the hidden layer is the log-sigmoid activation function a=1/(1 - e-n), and the transfer function in the output layer is the linear function a=n. (Idirs, 2014)

2.4 Mathematical Models for Prediction 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)

$$f'_{cD} \frac{D}{D+q} \text{ p} \qquad (2.12)$$

Where f^{i}_{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.

$$(f'_c)_t = \frac{t}{a+b.t}(f'_c)_{28d} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(2.13)}$$

Here, a and b are constants, $(f^i{}_c)_{28d}$ = 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 fc_{28} and the 7-day strength, fc_7 is taken to lie between (Shetty 2006),

$$\mathbf{f_{c28} = 1.4f_{c7} + 150} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(2.14)}$$

And

$$\mathbf{f_{c28} = 1.7f_{c7} + 850}(\boldsymbol{f_c}) \quad \ldots\ldots\ldots\ldots\ldots \quad \text{(2.15)}$$

Is being expressed in psi

$$\mathbf{f_c = Ax^{-B}}$$

Where (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:

$$\mathbf{f_{c28} = K_2(f_{c7})^{K_1}}$$

Where, fc_7 and fc_{28} 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).

CHAPTER THREE

RESEARCH METHODOLOGY

3.1 Materials

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 were obtained using the relation below

$$Strength = \frac{Load}{Area} \quad \ldots\ldots\ldots\ldots\ldots\ldots (3.1)$$

3.1.1 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).

3.1.2 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.

3.1.3 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.

The specific gravity of the fine aggregate was found to be 2.6. Particle size distribution was conducted in accordance with BS 812 (1985) and the fine aggregate was classified as zone-II according to BS882 (1992).

Table 3.1 and Figure 3.1 show the sieve analysis and particle size distribution profile respectively for fine and coarse aggregates.

Table 3.1: Sieve Analysis of Fine and Coarse Aggregates

Fine Aggregate		Coarse Aggregate	
Sieve size (mm)	Cumulative Passing (%)	Sieve size (mm)	CumulativePassing (%)
14	100	50	100
10	100	37	100
6.3	99.32	28	88
5	98.4	20	92.4
3.4	96.66	14	20.3
2	91.64	10	1.1
1.2	80.17	6	0.65
0.6	52.71	5	0.65
0.425	36.04	3.4	0.65
0.3	18.04	2	0.25
0.212	7.38	1.2	0.25
0.15	2.05		
0.075	0.37		
Passing 75 microns	0		

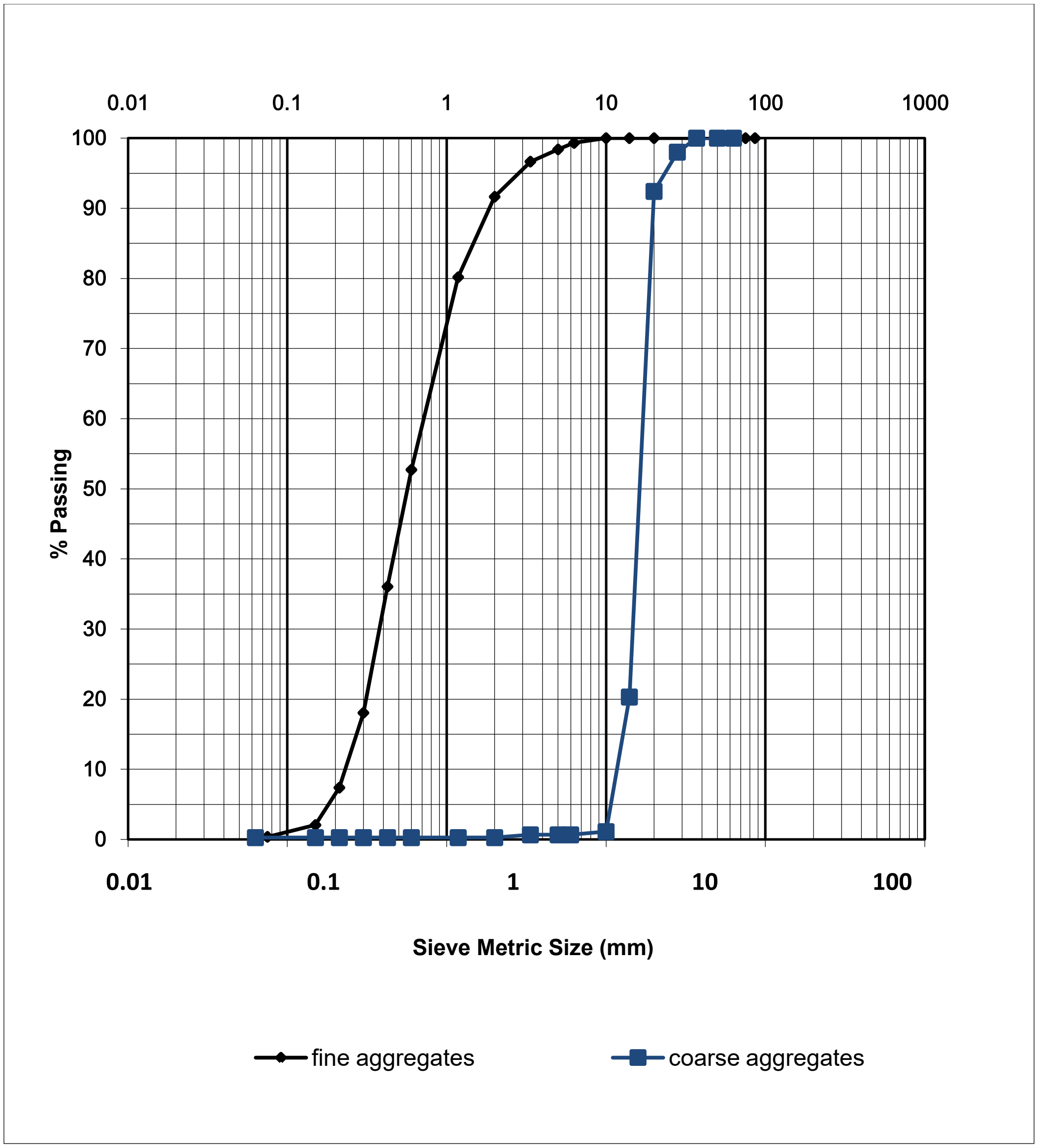


Figure 3.1: Particle size distribution for Fine and Coarse aggregates

3.1.4 Water

Clean tap water from Civil Engineering Department Laboratory, Bayero University Kano, was used throughout the experiment.

3.2 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 Table 3.2.

Table 3.2 Concrete Mix Proportion

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

3.3 Compressive Strength

The compressive strengths of the cubes were carried out using the mix proportions in Table 3.1 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 3.3

Table 3.3: Summary Laboratory Results

w/c ratio (Kg/m^3)	Cement (Kg/m^3)	Fine aggregate (Kg/m^3)	Coarse aggregate (Kg/m^3)	Average compressive strength (N/mm^2)	
				7^{th} Day	28^{th} Day
0.4	360.4	720.8	1441.7	24.9	38
0.5	348.8	697.6	1395.2	20.1	30.5
0.6	337.6	675.2	1350.4	16	23.7
0.65	332.2	664.5	1329	14.3	22.1

3.4 Network Development

The artificial neural network in this study was developed using MATLAB (R2011a) package. The input variables for the proposed neural network consist of water cement ratio (w/c), cement content, fine aggregate content, coarse aggregate content and 7th day compressive strength. The output variable is the 28th day compressive strength.

The six import variables (water cement ratio (w/c), cement content, fine aggregate content, coarse aggregate content and 7th day compressive strength) were arranged in Microsoft Excel sheet for easy importation to the Matlab environment. Using the *nnstart* command, time series tool which is best for data prediction was used. The import variables were imported and saved as Matlab file for training, validation and testing.

3.5 Neural Architecture

As stated in the methodology, ANN tool box in MATLAB (R2011a) was studied and used in the developing the network architecture. Input data in the form of 6-column matrix containing the input parameters (water content Kg/m^3, cement content Kg/m^3, fine aggregate Kg/m^3, coarse aggregate Kg/m^3 and 7th day compressive strength N/mm^2) were fed into the workspace. These automatically made the input neurons in the input layer to be six (6). The training algorithm adopted for the study is the Levenberg – Macquardt's and after several random trials, the number of neurons in the hidden layer for optimal convergence was found to be three. Since the output parameter is one (28th day compressive strength), the number of neuron in the output layer was one (1). The final network architecture for the study is shown in Figure 4.3.

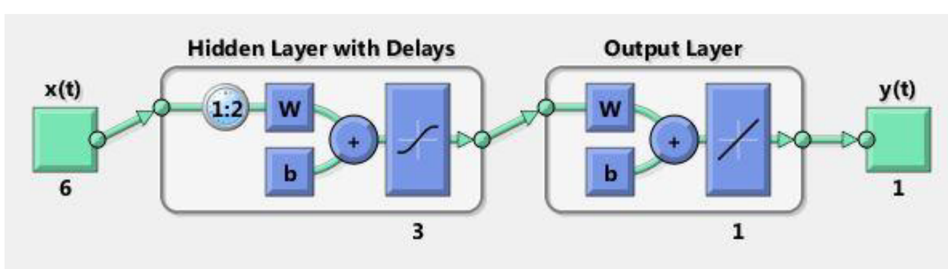


Figure 3.2: The final network architecture

Workflow showing the step by step of the Neural Network development processes is shown in Figure 3.2

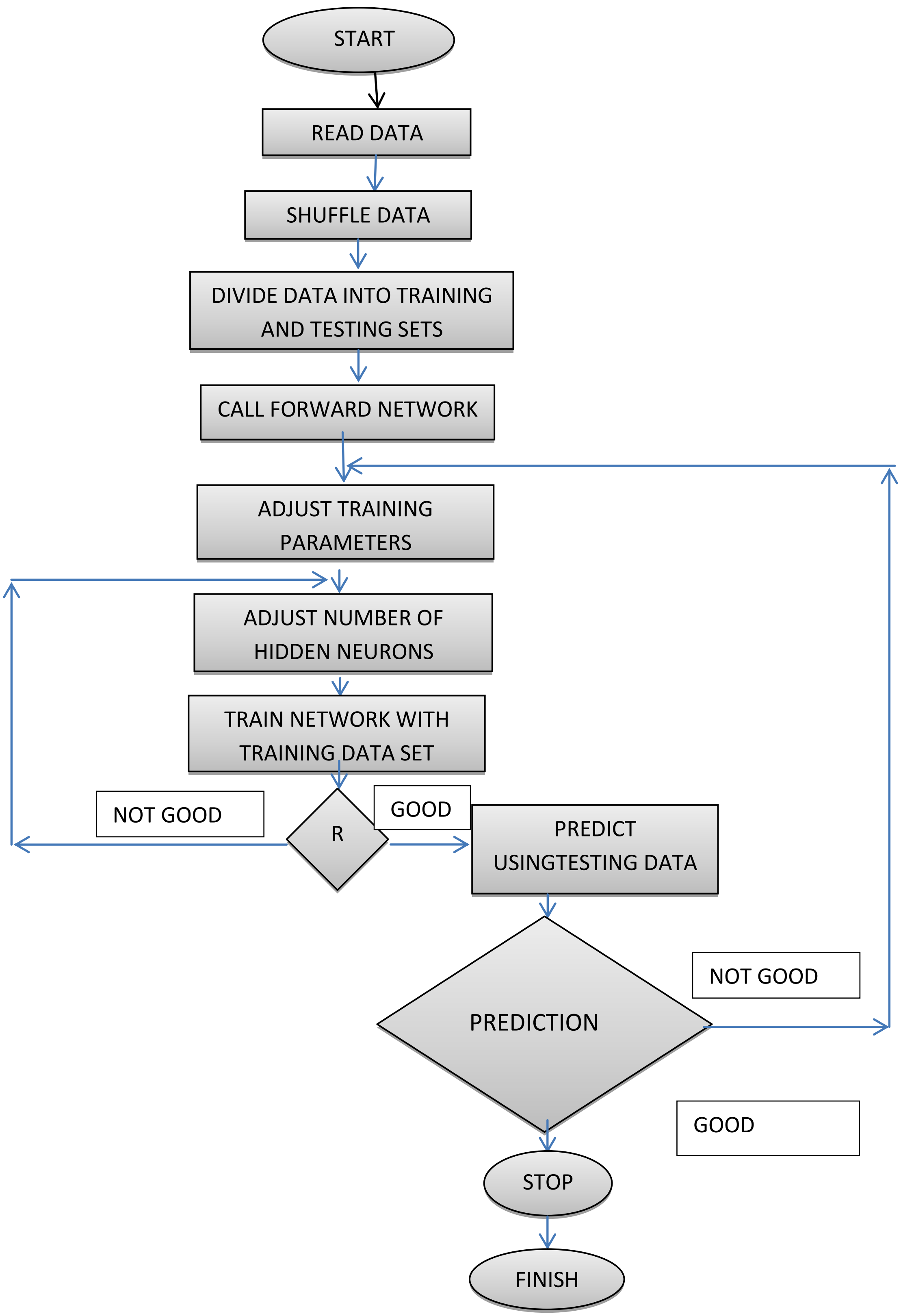


Figure 3.3: Flow chart for the NN Development

3.6 Network training, validation and testing

The imported data were randomized automatically by the system and divided into three. 55% for training, 15% for validation and 30% for testing were used. Thus among the 200 data sets for this study, 110 randomly collected data were used in the training stage, 30 for validation and the remaining 60 data set were used in testing the network. The network is trained and retrained to until it understand the relationship between the input variables and the 28th day compressive strength (output variable).

In order to develop the ANN model, it is common practice to divide the available in to three subsets: training set to construct the ANN model, Validation set and an independent set to estimate model performance. The data set was divided randomly in to three separate data sets. The data division ratio of 55% for training, 15% for validation and 30% for testing was used thus among the 200 data sets, 110 randomly collected data were used in the training stage, 30 for validation and the remaining 60 data set were used in testing the network.

The values of the input and output variables used in ANN model are obtained from the results of compressive strength test conducted in the laboratory as summarized in Appendix 1. Three hidden layer with 8 neurons was used in the architecture of multilayer neural network due to its minimum absolute percentage error values training and testing sets. Finally, the output layer neurons produced the network prediction results. In this study, the Levenberg-macquard's training algorithm was utilized in the feed-forward network. Back-propagation, as one of the most well-known training algorithm for the multilayer perception, which is a gradient descent technique that minimizes the error for a particular training pattern in which it adjusts the weights by small amount at a time. The non-linear sigmoid function which is the most suited for concrete modeling was used as the transfer function in the hidden layer. Momentum rate and learning rate values were determined and the model was trained through iterations. The trained model was tested with the input values and the results found were close to experiment results. The values of parameters used in this research are as follows:

- Number of input layer units = 6
- Number of hidden layer = 3
- Number of output layer unit = 1
- Learning cycle = 24

CHAPTER FOUR

RESULTS AND DISCUSSION

4.1 Preamble

This chapter presents the results of the laboratory tests for concrete cubes strengths in order to form the database of sets of data for use in the neural network modeling. The chapter also presents the findings on the suitability of ANN in the prediction of 28th day concrete compressive strength. It also discusses the general outcome of the results.

4.2 Compressive strength of concrete cubes

As stated in the methodology, concrete cubes were cast in 150mm by 150mm by 150mm steel mold at four different water cement ratios: 0.4, 0.5, 0.6, 0.65, and then cured for 7 days and 28 days. The prepared samples were then tested using compression machine and 7th and 28th day strength were obtained as shown in Table 4.1.

Table 4.1: Compressive strength and the various concrete mix constituent

Concrete Mix Constituent (Kg/m^{3})				**Compressive Strength (N/mm^2)**	
W/C ratio	Cement	Coarse aggregate	Fine aggregate	7th Day	28th Day
0.4	360.4	1441.7	720.8	24.9	38.0
0.5	348.8	1395.2	697.6	20.1	30.5
0.6	337.6	1350.4	675.2	16.0	23.7
0.65	332.2	1329.0	664.5	14.3	22.1

Figure (4.1) shows the relationship between compressive strength (N/mm^2) at 7th and 28th day with water-cement ratio, this shows an inverse relationship, where the compressive strength decreases with increase in water-cement ratio, hence the compressive strength increase with increase in cement content and decrease with increase in water content. Also from Table 4.1 it can be deduce that the compressive strength decrease with decrease in fine and coarse aggregate content, hence a direct relationship exist between compressive strength and aggregates content.

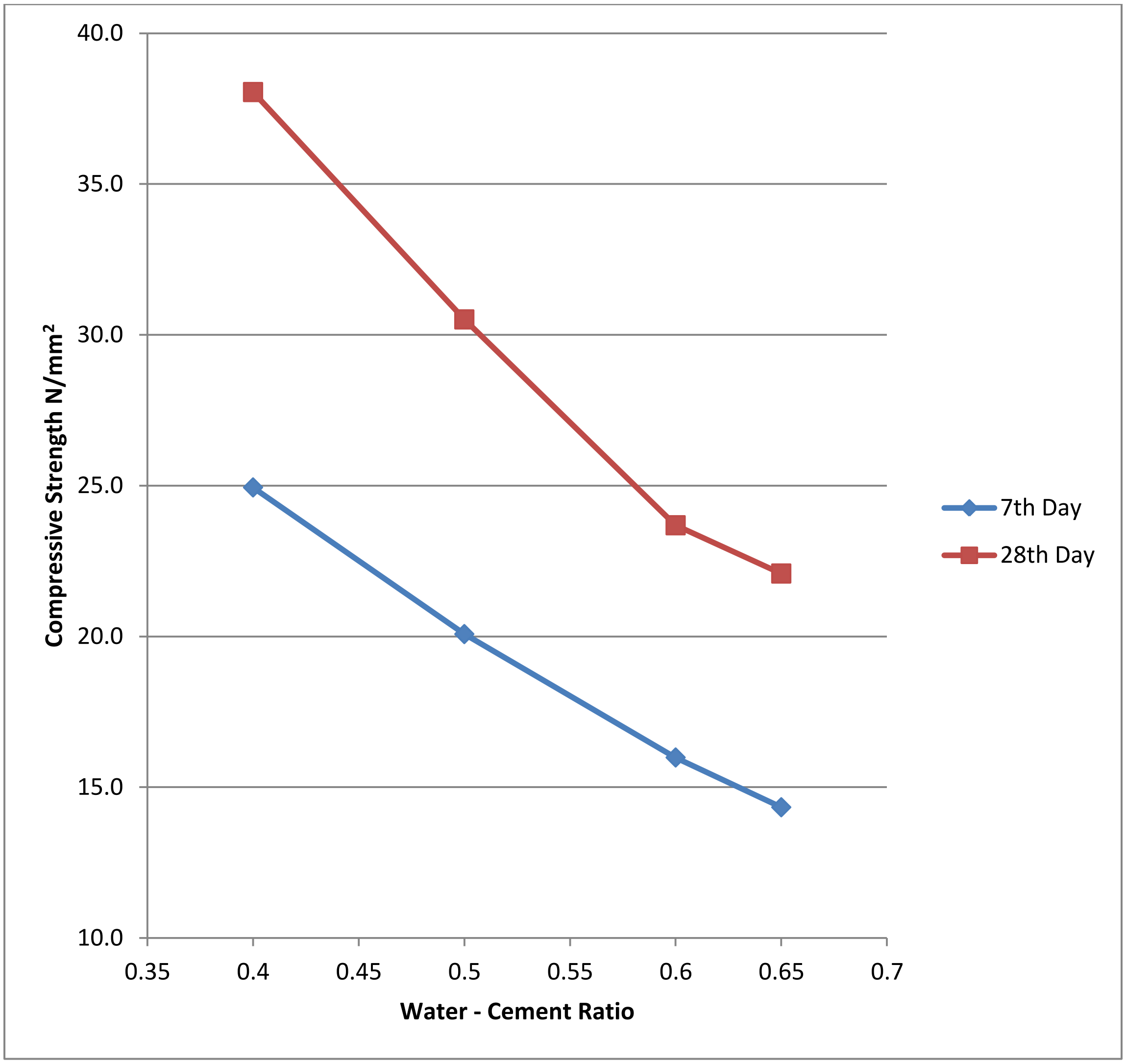


Figure 4.1: Compressive strength at different water-cement ratio

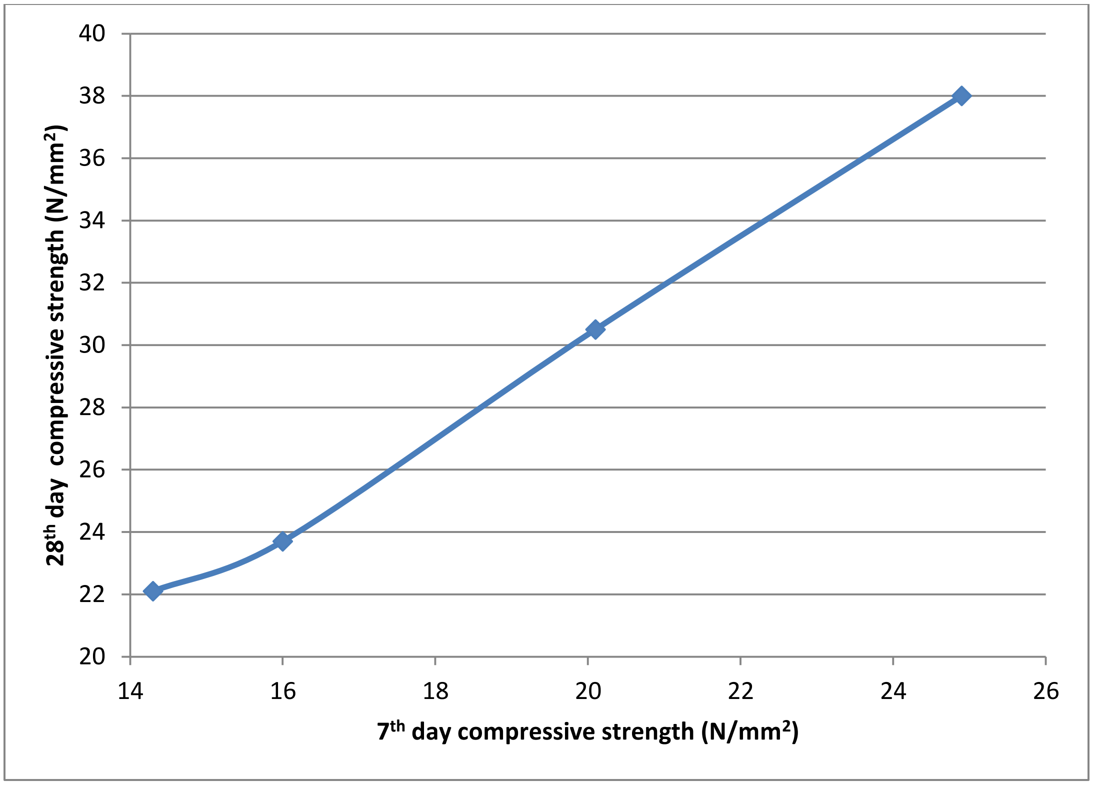


Figure 4.2: Relationship between 7th day and 28th day Compressive strength

Figure 4.2 shows an approximately linear relationship between the 7th day and the 28th day concrete strength, with the 28th day increasing with increase in the 7th day strength. From Figure 4.2 the relationship between the 28th day and 7th day concrete strength is defined by equation 4.1

$$f_{28} = 1.5344f_7 + 0.3092 \quad (4.1)$$

Where f_{28} = 28th day compressive strength

f_7 = 7th day compressive strength

Table 4.2: Comparison between experimental and mathematical model strengths at 28th day

Experimental result (N/mm^2)		**Shetty Model (N/mm^2)**	**$f_{28} = 1.534f_7 + 0.309$**
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

Table 4.2 shows comparison between the experimental 28th day strength and the 28th day strength obtained using the mathematical model $f_{c28} = 1.4f_{c7} + 150$ in psi (Shetty 2006), which is equivalent to $f_{c28} = 1.4f_{c7} + 1.0342$ in N/mm^2, which shows that experimental result slightly higher than the model result.

4.4 Results of ANN

The results of the network testing after training 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 at 28th day are shown in Figures 4.3 and 4.4

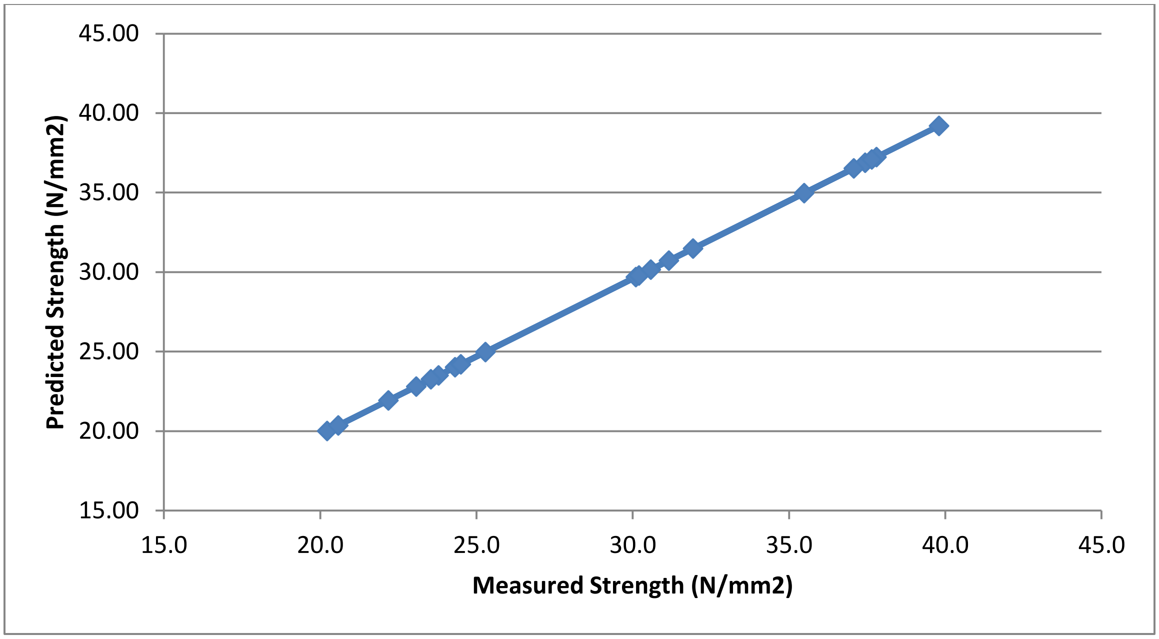


Figure 4.3 Relationship between measured and predicted 28th day compressive strength

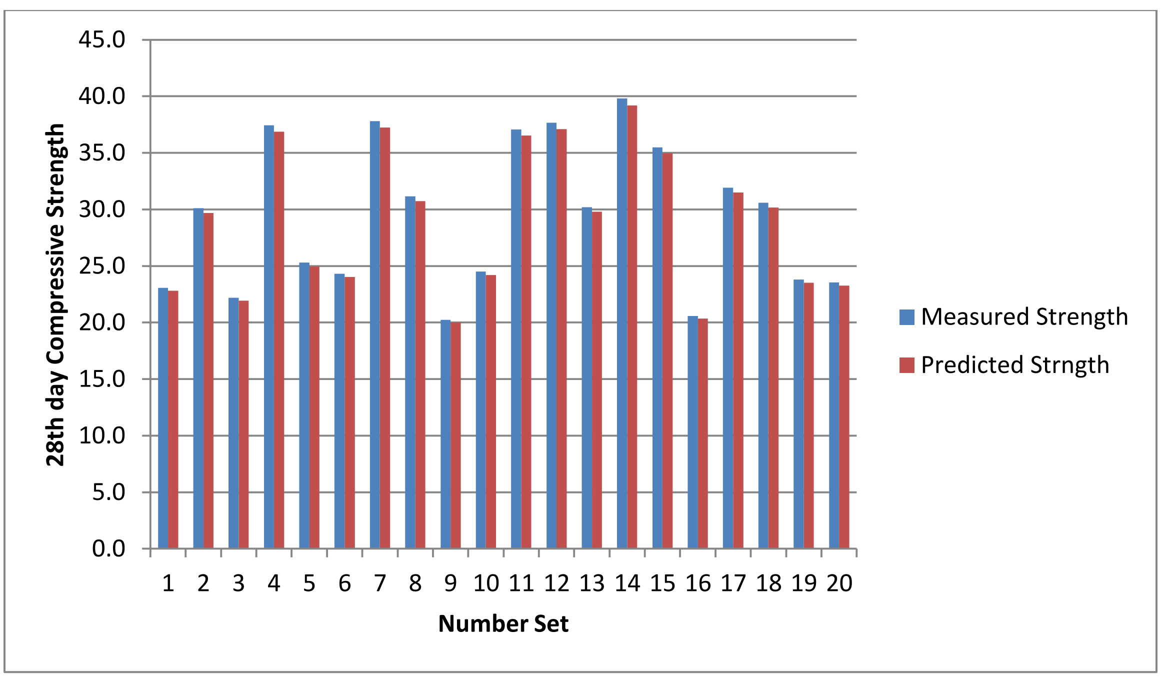


Figure 4.4 Relationship between measured and predicted 28th day compressive strength

In general, the R value for the training data set was larger than that for the testing set, i.e., the neural network made better prediction for the training data sets than the testing data set. The combination of transfer function composed of tan-sigmoid and linear function gives a good result. Figure 4.5 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 data (R = 0.99482) and the general correlation of R = 0.99675.

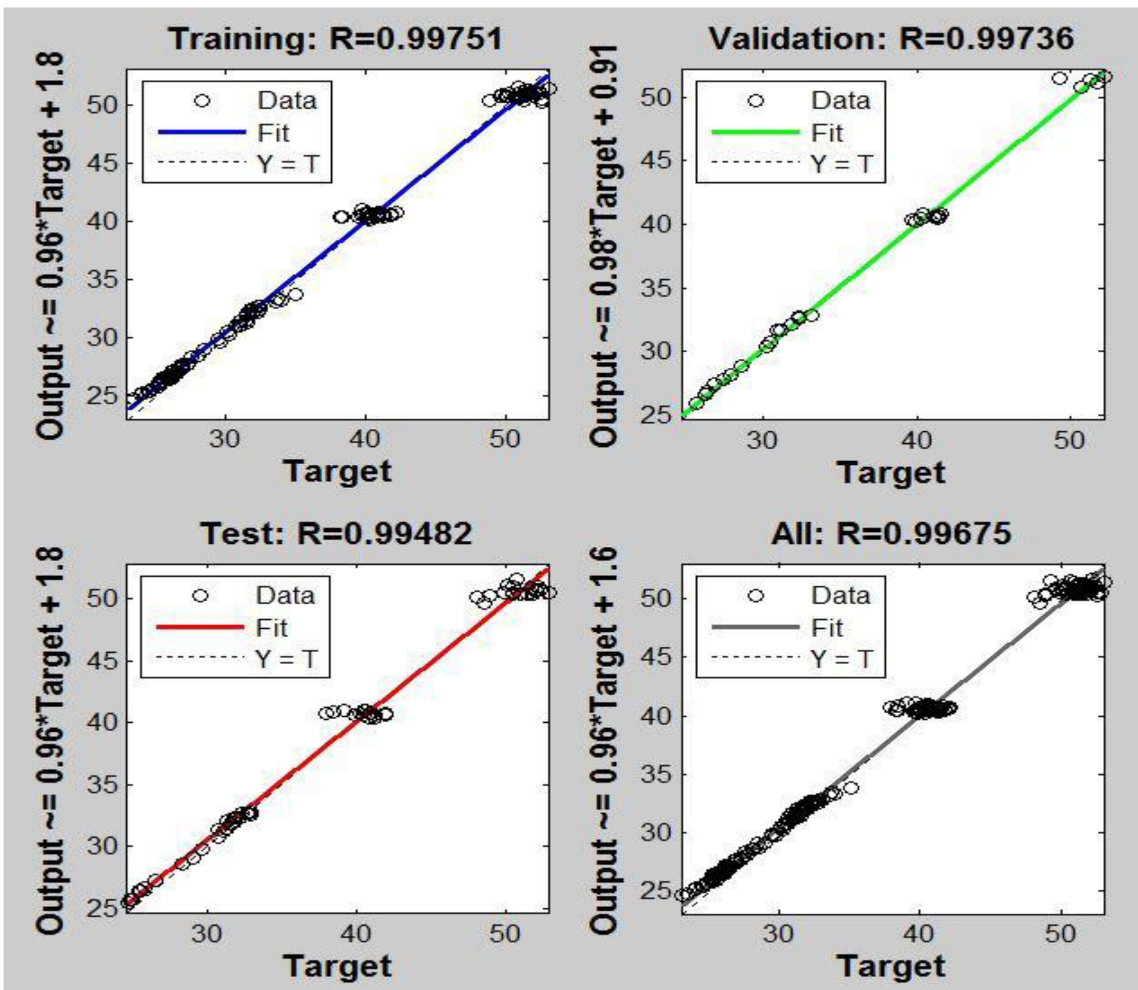


Figure 4.5: Correlation between Measured and ANN Predicted Result

CHAPTER FIVE

CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

The objective of this study was to make a predictive model correlate the 7^{th} day compressive strength with the 28^{th} day compressive strength. From the study, the following conclusions are drawn;

1. The 28^{th} day compressive strength was found to be directly proportional to 7^{th} day compressive strength.
2. Artificial neural network toolbox based in the commercial software, MATLAB (R2011a) was used to develop predictive model. The input layers in this work consist of 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 28^{th} 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 quit efficient in determining the 28^{th} 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

5.2 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 28^{th} day. Hence, further studies are recommended to cover concrete compositions and conditions.

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APPENDIX:

DETAILED RESULTS DATA BASE

Table A: Detailed Compressive Strength Test Result

S/N	W:C Ratio	water (Kg/m^3)	Cement (Kg/m^3)	Fine agg (Kg/m^3	Co agg (Kg/m^3)	7day (N/mm^2	28day (N/mm^2)
1	0.4	144.2	360.4	720.8	1441.7	23.8	37.4
2	0.4	144.2	360.4	720.8	1441.7	25.0	37.8
3	0.4	144.2	360.4	720.8	1441.7	26.1	37.1
4	0.4	144.2	360.4	720.8	1441.7	26.3	37.6
5	0.4	144.2	360.4	720.8	1441.7	25.3	39.8
6	0.4	144.2	360.4	720.8	1441.7	22.3	35.5
7	0.4	144.2	360.4	720.8	1441.7	24.9	36.7
8	0.4	144.2	360.4	720.8	1441.7	24.0	37.9
9	0.4	144.2	360.4	720.8	1441.7	24.7	39.5
10	0.4	144.2	360.4	720.8	1441.7	23.5	37.1
11	0.4	144.2	360.4	720.8	1441.7	24.1	37.2
12	0.4	144.2	360.4	720.8	1441.7	25.3	38.7
13	0.4	144.2	360.4	720.8	1441.7	26.0	40.0
14	0.4	144.2	360.4	720.8	1441.7	25.9	38.7
15	0.4	144.2	360.4	720.8	1441.7	24.4	39.3
16	0.4	144.2	360.4	720.8	1441.7	24.6	38.4
17	0.4	144.2	360.4	720.8	1441.7	26.0	36.3
18	0.4	144.2	360.4	720.8	1441.7	24.8	37.0
19	0.4	144.2	360.4	720.8	1441.7	25.2	37.7
20	0.4	144.2	360.4	720.8	1441.7	24.7	38.4
21	0.4	144.2	360.4	720.8	1441.7	25.8	37.4
22	0.4	144.2	360.4	720.8	1441.7	24.8	39.0
23	0.4	144.2	360.4	720.8	1441.7	25.6	37.8
24	0.4	144.2	360.4	720.8	1441.7	24.6	38.8
25	0.4	144.2	360.4	720.8	1441.7	22.8	35.1
26	0.4	144.2	360.4	720.8	1441.7	25.1	39.0
27	0.4	144.2	360.4	720.8	1441.7	24.5	38.0
28	0.4	144.2	360.4	720.8	1441.7	25.5	36.9
29	0.4	144.2	360.4	720.8	1441.7	24.6	39.6
30	0.4	144.2	360.4	720.8	1441.7	25.9	39.1
31	0.4	144.2	360.4	720.8	1441.7	25.0	39.4
32	0.4	144.2	360.4	720.8	1441.7	24.8	38.4
33	0.4	144.2	360.4	720.8	1441.7	23.8	35.9
34	0.4	144.2	360.4	720.8	1441.7	25.2	38.3
35	0.4	144.2	360.4	720.8	1441.7	24.1	35.9
36	0.4	144.2	360.4	720.8	1441.7	24.3	38.0
37	0.4	144.2	360.4	720.8	1441.7	24.3	38.2
38	0.4	144.2	360.4	720.8	1441.7	25.3	38.8
39	0.4	144.2	360.4	720.8	1441.7	24.7	38.9

S/N	W:C Ratio	water (Kg/m^3)	Cement (Kg/m^3)	Fine agg (Kg/m^3	Co agg (Kg/m^3)	7day (N/mm^2	28day (N/mm^2)
40	0.4	144.2	360.4	720.8	1441.7	26.5	39.1
41	0.4	144.2	360.4	720.8	1441.7	25.1	38.7
42	0.4	144.2	360.4	720.8	1441.7	24.6	37.9
43	0.4	144.2	360.4	720.8	1441.7	24.9	39.2
44	0.4	144.2	360.4	720.8	1441.7	25.7	38.4
45	0.4	144.2	360.4	720.8	1441.7	26.5	39.2
46	0.4	144.2	360.4	720.8	1441.7	23.5	37.5
47	0.4	144.2	360.4	720.8	1441.7	26.2	37.8
48	0.4	144.2	360.4	720.8	1441.7	25.8	36.7
49	0.4	144.2	360.4	720.8	1441.7	25.0	38.6
50	0.4	144.2	360.4	720.8	1441.7	24.9	38.4
51	0.5	174.4	348.8	697.6	1395.2	19.2	30.1
52	0.5	174.4	348.8	697.6	1395.2	18.9	31.2
53	0.5	174.4	348.8	697.6	1395.2	19.4	30.2
54	0.5	174.4	348.8	697.6	1395.2	19.7	31.9
55	0.5	174.4	348.8	697.6	1395.2	19.7	30.6
56	0.5	174.4	348.8	697.6	1395.2	20.6	28.2
57	0.5	174.4	348.8	697.6	1395.2	20.5	29.7
58	0.5	174.4	348.8	697.6	1395.2	21.6	32.0
59	0.5	174.4	348.8	697.6	1395.2	21.2	31.2
60	0.5	174.4	348.8	697.6	1395.2	19.4	31.6
61	0.5	174.4	348.8	697.6	1395.2	19.8	29.1
62	0.5	174.4	348.8	697.6	1395.2	20.6	30.5
63	0.5	174.4	348.8	697.6	1395.2	20.9	29.7
64	0.5	174.4	348.8	697.6	1395.2	20.1	31.3
65	0.5	174.4	348.8	697.6	1395.2	20.3	30.9
66	0.5	174.4	348.8	697.6	1395.2	19.7	30.2
67	0.5	174.4	348.8	697.6	1395.2	19.0	31.2
68	0.5	174.4	348.8	697.6	1395.2	19.9	31.8
69	0.5	174.4	348.8	697.6	1395.2	20.4	30.5
70	0.5	174.4	348.8	697.6	1395.2	21.4	31.0
71	0.5	174.4	348.8	697.6	1395.2	18.6	30.3
72	0.5	174.4	348.8	697.6	1395.2	21.3	29.9
73	0.5	174.4	348.8	697.6	1395.2	21.2	29.9
74	0.5	174.4	348.8	697.6	1395.2	20.3	28.4
75	0.5	174.4	348.8	697.6	1395.2	19.6	30.3
76	0.5	174.4	348.8	697.6	1395.2	19.5	29.5
77	0.5	174.4	348.8	697.6	1395.2	20.2	29.9
78	0.5	174.4	348.8	697.6	1395.2	19.3	32.0
79	0.5	174.4	348.8	697.6	1395.2	19.9	31.2
80	0.5	174.4	348.8	697.6	1395.2	21.1	30.8
81	0.5	174.4	348.8	697.6	1395.2	21.6	27.9

S/N	W:C Ratio	water (Kg/m^3)	Cement (Kg/m^3)	Fine agg (Kg/m^3	Co agg (Kg/m^3)	7day (N/mm^2	28day (N/mm^2)
82	0.5	174.4	348.8	697.6	1395.2	21.1	30.2
83	0.5	174.4	348.8	697.6	1395.2	19.7	30.9
84	0.5	174.4	348.8	697.6	1395.2	18.3	30.4
85	0.5	174.4	348.8	697.6	1395.2	18.9	30.8
86	0.5	174.4	348.8	697.6	1395.2	21.1	30.1
87	0.5	174.4	348.8	697.6	1395.2	19.5	31.4
88	0.5	174.4	348.8	697.6	1395.2	20.9	32.2
89	0.5	174.4	348.8	697.6	1395.2	20.2	31.8
90	0.5	174.4	348.8	697.6	1395.2	20.8	31.3
91	0.5	174.4	348.8	697.6	1395.2	18.0	31.5
92	0.5	174.4	348.8	697.6	1395.2	18.9	29.9
93	0.5	174.4	348.8	697.6	1395.2	20.6	30.5
94	0.5	174.4	348.8	697.6	1395.2	21.4	31.1
95	0.5	174.4	348.8	697.6	1395.2	20.4	30.4
96	0.5	174.4	348.8	697.6	1395.2	20.2	28.4
97	0.5	174.4	348.8	697.6	1395.2	20.7	29.8
98	0.5	174.4	348.8	697.6	1395.2	18.3	30.3
99	0.5	174.4	348.8	697.6	1395.2	20.0	30.8
100	0.5	174.4	348.8	697.6	1395.2	20.1	31.4
101	0.6	202.6	337.6	675.2	1350.4	15.3	23.1
102	0.6	202.6	337.6	675.2	1350.4	14.4	22.2
103	0.6	202.6	337.6	675.2	1350.4	17.5	25.3
104	0.6	202.6	337.6	675.2	1350.4	16.5	24.3
105	0.6	202.6	337.6	675.2	1350.4	16.9	24.5
106	0.6	202.6	337.6	675.2	1350.4	12.8	20.6
107	0.6	202.6	337.6	675.2	1350.4	15.7	23.5
108	0.6	202.6	337.6	675.2	1350.4	13.7	21.5
109	0.6	202.6	337.6	675.2	1350.4	16.3	23.9
110	0.6	202.6	337.6	675.2	1350.4	17.3	25.1
111	0.6	202.6	337.6	675.2	1350.4	15.6	23.2
112	0.6	202.6	337.6	675.2	1350.4	16.0	23.8
113	0.6	202.6	337.6	675.2	1350.4	16.3	23.9
114	0.6	202.6	337.6	675.2	1350.4	15.9	23.7
115	0.6	202.6	337.6	675.2	1350.4	15.4	23.0
116	0.6	202.6	337.6	675.2	1350.4	14.6	22.2
117	0.6	202.6	337.6	675.2	1350.4	16.4	24.0
118	0.6	202.6	337.6	675.2	1350.4	16.7	24.3
119	0.6	202.6	337.6	675.2	1350.4	17.9	25.7
120	0.6	202.6	337.6	675.2	1350.4	15.8	23.4
121	0.6	202.6	337.6	675.2	1350.4	13.2	21.0
122	0.6	202.6	337.6	675.2	1350.4	15.6	23.2
123	0.6	202.6	337.6	675.2	1350.4	15.4	23.0

S/N	W:C Ratio	water (Kg/m^3)	Cement (Kg/m^3)	Fine agg (Kg/m^3	Co agg (Kg/m^3)	7day (N/mm^2	28day (N/mm^2)
124	0.6	202.6	337.6	675.2	1350.4	15.0	22.8
125	0.6	202.6	337.6	675.2	1350.4	16.3	23.9
126	0.6	202.6	337.6	675.2	1350.4	14.4	22.2
127	0.6	202.6	337.6	675.2	1350.4	17.1	24.9
128	0.6	202.6	337.6	675.2	1350.4	16.2	24.0
129	0.6	202.6	337.6	675.2	1350.4	15.9	23.5
130	0.6	202.6	337.6	675.2	1350.4	16.0	23.6
131	0.6	202.6	337.6	675.2	1350.4	16.7	24.5
132	0.6	202.6	337.6	675.2	1350.4	16.0	23.8
133	0.6	202.6	337.6	675.2	1350.4	15.0	22.6
134	0.6	202.6	337.6	675.2	1350.4	13.9	21.7
135	0.6	202.6	337.6	675.2	1350.4	19.3	27.1
136	0.6	202.6	337.6	675.2	1350.4	16.5	24.1
137	0.6	202.6	337.6	675.2	1350.4	15.2	22.8
138	0.6	202.6	337.6	675.2	1350.4	18.2	26.0
139	0.6	202.6	337.6	675.2	1350.4	16.5	24.3
140	0.6	202.6	337.6	675.2	1350.4	17.1	24.7
141	0.6	202.6	337.6	675.2	1350.4	15.8	23.6
142	0.6	202.6	337.6	675.2	1350.4	15.0	22.6
143	0.6	202.6	337.6	675.2	1350.4	16.0	23.6
144	0.6	202.6	337.6	675.2	1350.4	16.6	24.2
145	0.6	202.6	337.6	675.2	1350.4	16.7	24.3
146	0.6	202.6	337.6	675.2	1350.4	15.5	23.1
147	0.6	202.6	337.6	675.2	1350.4	17.8	25.6
148	0.6	202.6	337.6	675.2	1350.4	17.0	24.8
149	0.6	202.6	337.6	675.2	1350.4	17.0	24.6
150	0.6	202.6	337.6	675.2	1350.4	14.8	22.4
151	0.65	216.0	332.2	664.5	1329.0	12.4	20.2
152	0.65	216.0	332.2	664.5	1329.0	16.0	23.8
153	0.65	216.0	332.2	664.5	1329.0	13.6	21.3
154	0.65	216.0	332.2	664.5	1329.0	13.4	21.1
155	0.65	216.0	332.2	664.5	1329.0	11.3	19.1
156	0.65	216.0	332.2	664.5	1329.0	13.2	20.9
157	0.65	216.0	332.2	664.5	1329.0	14.5	22.2
158	0.65	216.0	332.2	664.5	1329.0	15.1	22.8
159	0.65	216.0	332.2	664.5	1329.0	13.0	20.7
160	0.65	216.0	332.2	664.5	1329.0	13.8	21.6
161	0.65	216.0	332.2	664.5	1329.0	14.4	22.2
162	0.65	216.0	332.2	664.5	1329.0	17.8	25.6
163	0.65	216.0	332.2	664.5	1329.0	13.7	21.4
164	0.65	216.0	332.2	664.5	1329.0	15.8	23.6
165	0.65	216.0	332.2	664.5	1329.0	14.6	22.3

S/N	W:C Ratio	water (Kg/m^3)	Cement (Kg/m^3)	Fine agg (Kg/m^3	Co agg (Kg/m^3)	7day (N/mm^2	28day (N/mm^2)
166	0.65	216.0	332.2	664.5	1329.0	14.2	21.9
167	0.65	216.0	332.2	664.5	1329.0	14.5	22.2
168	0.65	216.0	332.2	664.5	1329.0	16.7	24.5
169	0.65	216.0	332.2	664.5	1329.0	14.2	21.9
170	0.65	216.0	332.2	664.5	1329.0	16.4	24.2
171	0.65	216.0	332.2	664.5	1329.0	14.5	22.3
172	0.65	216.0	332.2	664.5	1329.0	12.9	20.7
173	0.65	216.0	332.2	664.5	1329.0	15.2	23.0
174	0.65	216.0	332.2	664.5	1329.0	14.7	22.4
175	0.65	216.0	332.2	664.5	1329.0	12.8	20.5
176	0.65	216.0	332.2	664.5	1329.0	12.2	20.0
177	0.65	216.0	332.2	664.5	1329.0	15.2	22.9
178	0.65	216.0	332.2	664.5	1329.0	13.2	20.9
179	0.65	216.0	332.2	664.5	1329.0	16.3	24.1
180	0.65	216.0	332.2	664.5	1329.0	15.6	23.4
181	0.65	216.0	332.2	664.5	1329.0	15.5	23.3
182	0.65	216.0	332.2	664.5	1329.0	14.9	22.6
183	0.65	216.0	332.2	664.5	1329.0	14.9	22.6
184	0.65	216.0	332.2	664.5	1329.0	15.0	22.8
185	0.65	216.0	332.2	664.5	1329.0	14.5	22.2
186	0.65	216.0	332.2	664.5	1329.0	14.0	21.7
187	0.65	216.0	332.2	664.5	1329.0	15.3	23.0
188	0.65	216.0	332.2	664.5	1329.0	14.2	22.0
189	0.65	216.0	332.2	664.5	1329.0	13.5	21.3
190	0.65	216.0	332.2	664.5	1329.0	13.8	21.5
191	0.65	216.0	332.2	664.5	1329.0	14.8	22.5
192	0.65	216.0	332.2	664.5	1329.0	13.6	21.3
193	0.65	216.0	332.2	664.5	1329.0	15.0	22.8
194	0.65	216.0	332.2	664.5	1329.0	14.1	21.8
195	0.65	216.0	332.2	664.5	1329.0	13.8	21.5
196	0.65	216.0	332.2	664.5	1329.0	14.7	22.5
197	0.65	216.0	332.2	664.5	1329.0	14.3	22.1
198	0.65	216.0	332.2	664.5	1329.0	14.5	22.3
199	0.65	216.0	332.2	664.5	1329.0	11.7	19.5
200	0.65	216.0	332.2	664.5	1329.0	12.9	20.7

Table B: Training and Validation Data

s/n	W:C Ratio	water (Kg/m^3)	Cement (Kg/m^3)	Fine agg Kg/m^3	Co agg Kg/m^3	7day (N/mm^2)	28day(N/mm^2)
1	0.6	202.6	337.6	675.2	1350.4	15.3	23.1
2	0.5	174.4	348.8	697.6	1395.2	19.2	30.1
3	0.6	202.6	337.6	675.2	1350.4	14.4	22.2
4	0.4	144.2	360.4	720.8	1441.7	23.8	37.4
5	0.6	202.6	337.6	675.2	1350.4	17.5	25.3
6	0.6	202.6	337.6	675.2	1350.4	16.5	24.3
7	0.4	144.2	360.4	720.8	1441.7	25.0	37.8
8	0.5	174.4	348.8	697.6	1395.2	18.9	31.2
9	6.5	216.0	332.2	664.5	1329.0	12.4	20.2
10	0.6	202.6	337.6	675.2	1350.4	16.9	24.5
11	0.4	144.2	360.4	720.8	1441.7	26.1	37.1
12	0.4	144.2	360.4	720.8	1441.7	26.3	37.6
13	0.5	174.4	348.8	697.6	1395.2	19.4	30.2
14	0.4	144.2	360.4	720.8	1441.7	25.3	39.8
15	0.4	144.2	360.4	720.8	1441.7	22.3	35.5
16	0.6	202.6	337.6	675.2	1350.4	12.8	20.6
17	0.5	174.4	348.8	697.6	1395.2	19.7	31.9
18	0.5	174.4	348.8	697.6	1395.2	19.7	30.6
19	6.5	216.0	332.2	664.5	1329.0	16.0	23.8
20	0.6	202.6	337.6	675.2	1350.4	15.7	23.5
21	6.5	216.0	332.2	664.5	1329.0	13.6	21.3
22	0.6	202.6	337.6	675.2	1350.4	13.7	21.5
23	0.5	174.4	348.8	697.6	1395.2	20.6	28.2
24	0.4	144.2	360.4	720.8	1441.7	24.9	36.7
25	0.5	174.4	348.8	697.6	1395.2	20.5	29.7
26	0.6	202.6	337.6	675.2	1350.4	16.3	23.9
27	0.5	174.4	348.8	697.6	1395.2	21.6	32.0
28	0.6	202.6	337.6	675.2	1350.4	17.3	25.1
29	6.5	216.0	332.2	664.5	1329.0	13.4	21.1
30	0.6	202.6	337.6	675.2	1350.4	15.6	23.2
31	0.6	202.6	337.6	675.2	1350.4	16.0	23.8
32	6.5	216.0	332.2	664.5	1329.0	11.3	19.1
33	0.6	202.6	337.6	675.2	1350.4	16.3	23.9
34	0.6	202.6	337.6	675.2	1350.4	15.9	23.7
35	0.5	174.4	348.8	697.6	1395.2	21.2	31.2
36	0.4	144.2	360.4	720.8	1441.7	24.0	37.9
37	0.4	144.2	360.4	720.8	1441.7	24.7	39.5
38	0.4	144.2	360.4	720.8	1441.7	23.5	37.1
39	6.5	216.0	332.2	664.5	1329.0	13.2	20.9
40	0.5	174.4	348.8	697.6	1395.2	19.4	31.6

s/n	W:C Ratio	water (Kg/m^3)	Cement (Kg/m^3)	Fine agg Kg/m^3	Co agg Kg/m^3	7day (N/mm^2)	28day(N/mm^2)
41	0.6	202.6	337.6	675.2	1350.4	15.4	23.0
42	0.4	144.2	360.4	720.8	1441.7	24.1	37.2
43	0.4	144.2	360.4	720.8	1441.7	25.3	38.7
44	0.5	174.4	348.8	697.6	1395.2	19.8	29.1
45	0.5	174.4	348.8	697.6	1395.2	20.6	30.5
46	6.5	216.0	332.2	664.5	1329.0	14.5	22.2
47	0.4	144.2	360.4	720.8	1441.7	26.0	40.0
48	0.5	174.4	348.8	697.6	1395.2	20.9	29.7
49	0.5	174.4	348.8	697.6	1395.2	20.1	31.3
50	0.6	202.6	337.6	675.2	1350.4	14.6	22.2
51	0.5	174.4	348.8	697.6	1395.2	20.3	30.9
52	0.4	144.2	360.4	720.8	1441.7	25.9	38.7
53	0.6	202.6	337.6	675.2	1350.4	16.4	24.0
54	6.5	216.0	332.2	664.5	1329.0	15.1	22.8
55	0.5	174.4	348.8	697.6	1395.2	19.7	30.2
56	6.5	216.0	332.2	664.5	1329.0	13.0	20.7
57	0.5	174.4	348.8	697.6	1395.2	19.0	31.2
58	0.5	174.4	348.8	697.6	1395.2	19.9	31.8
59	0.4	144.2	360.4	720.8	1441.7	24.4	39.3
60	0.6	202.6	337.6	675.2	1350.4	16.7	24.3
61	0.4	144.2	360.4	720.8	1441.7	24.6	38.4
62	0.5	174.4	348.8	697.6	1395.2	20.4	30.5
63	0.5	174.4	348.8	697.6	1395.2	21.4	31.0
64	0.6	202.6	337.6	675.2	1350.4	17.9	25.7
65	0.4	144.2	360.4	720.8	1441.7	26.0	36.3
66	0.4	144.2	360.4	720.8	1441.7	24.8	37.0
67	0.5	174.4	348.8	697.6	1395.2	18.6	30.3
68	0.6	202.6	337.6	675.2	1350.4	15.8	23.4
69	6.5	216.0	332.2	664.5	1329.0	13.8	21.6
70	0.6	202.6	337.6	675.2	1350.4	13.2	21.0
71	0.4	144.2	360.4	720.8	1441.7	25.2	37.7
72	0.6	202.6	337.6	675.2	1350.4	15.6	23.2
73	0.6	202.6	337.6	675.2	1350.4	15.4	23.0
74	6.5	216.0	332.2	664.5	1329.0	14.4	22.2
75	0.6	202.6	337.6	675.2	1350.4	15.0	22.8
76	6.5	216.0	332.2	664.5	1329.0	17.8	25.6
77	0.5	174.4	348.8	697.6	1395.2	21.3	29.9
78	6.5	216.0	332.2	664.5	1329.0	13.7	21.4
79	0.6	202.6	337.6	675.2	1350.4	16.3	23.9
80	0.4	144.2	360.4	720.8	1441.7	24.7	38.4
81	6.5	216.0	332.2	664.5	1329.0	15.8	23.6
82	6.5	216.0	332.2	664.5	1329.0	14.6	22.3

s/n	W:C Ratio	water (Kg/m^3)	Cement (Kg/m^3)	Fine agg Kg/m^3	Co agg Kg/m^3	7day (N/mm^2)	28day(N/mm^2)
83	6.5	216.0	332.2	664.5	1329.0	14.2	21.9
84	6.5	216.0	332.2	664.5	1329.0	14.5	22.2
85	6.5	216.0	332.2	664.5	1329.0	16.7	24.5
86	0.5	174.4	348.8	697.6	1395.2	21.2	29.9
87	0.6	202.6	337.6	675.2	1350.4	14.4	22.2
88	6.5	216.0	332.2	664.5	1329.0	14.2	21.9
89	6.5	216.0	332.2	664.5	1329.0	16.4	24.2
90	6.5	216.0	332.2	664.5	1329.0	14.5	22.3
91	0.6	202.6	337.6	675.2	1350.4	17.1	24.9
92	6.5	216.0	332.2	664.5	1329.0	12.9	20.7
93	0.5	174.4	348.8	697.6	1395.2	20.3	28.4
94	6.5	216.0	332.2	664.5	1329.0	15.2	23.0
95	6.5	216.0	332.2	664.5	1329.0	14.7	22.4
96	0.5	174.4	348.8	697.6	1395.2	19.6	30.3
97	0.6	202.6	337.6	675.2	1350.4	16.2	24.0
98	0.6	202.6	337.6	675.2	1350.4	15.9	23.5
99	0.4	144.2	360.4	720.8	1441.7	25.8	37.4
100	0.4	144.2	360.4	720.8	1441.7	24.8	39.0
101	0.6	202.6	337.6	675.2	1350.4	16.0	23.6
102	6.5	216.0	332.2	664.5	1329.0	12.8	20.5
103	6.5	216.0	332.2	664.5	1329.0	12.2	20.0
104	0.6	202.6	337.6	675.2	1350.4	16.7	24.5
105	0.5	174.4	348.8	697.6	1395.2	19.5	29.5
106	6.5	216.0	332.2	664.5	1329.0	15.2	22.9
107	0.4	144.2	360.4	720.8	1441.7	25.6	37.8
108	0.6	202.6	337.6	675.2	1350.4	16.0	23.8
109	0.5	174.4	348.8	697.6	1395.2	20.2	29.9
110	0.4	144.2	360.4	720.8	1441.7	24.6	38.8
111	0.5	174.4	348.8	697.6	1395.2	19.3	32.0
112	0.4	144.2	360.4	720.8	1441.7	22.8	35.1
113	6.5	216.0	332.2	664.5	1329.0	13.2	20.9
114	0.4	144.2	360.4	720.8	1441.7	25.1	39.0
115	0.4	144.2	360.4	720.8	1441.7	24.5	38.0
116	6.5	216.0	332.2	664.5	1329.0	16.3	24.1
117	6.5	216.0	332.2	664.5	1329.0	15.6	23.4
118	0.5	174.4	348.8	697.6	1395.2	19.9	31.2
119	0.6	202.6	337.6	675.2	1350.4	15.0	22.6
120	0.4	144.2	360.4	720.8	1441.7	25.5	36.9
121	6.5	216.0	332.2	664.5	1329.0	15.5	23.3
122	0.5	174.4	348.8	697.6	1395.2	21.1	30.8
123	0.4	144.2	360.4	720.8	1441.7	24.6	39.6
124	0.5	174.4	348.8	697.6	1395.2	21.6	27.9

s/n	W:C Ratio	water (Kg/m^3)	Cement (Kg/m^3)	Fine agg Kg/m^3	Co agg Kg/m^3	7day (N/mm^2)	28day(N/mm^2)
125	0.4	144.2	360.4	720.8	1441.7	25.9	39.1
126	0.5	174.4	348.8	697.6	1395.2	21.1	30.2
127	0.4	144.2	360.4	720.8	1441.7	25.0	39.4
128	0.4	144.2	360.4	720.8	1441.7	24.8	38.4
129	0.4	144.2	360.4	720.8	1441.7	23.8	35.9
130	0.6	202.6	337.6	675.2	1350.4	13.9	21.7
131	6.5	216.0	332.2	664.5	1329.0	14.9	22.6
132	6.5	216.0	332.2	664.5	1329.0	14.9	22.6
133	0.6	202.6	337.6	675.2	1350.4	19.3	27.1
134	0.5	174.4	348.8	697.6	1395.2	19.7	30.9
135	0.4	144.2	360.4	720.8	1441.7	25.2	38.3
136	0.5	174.4	348.8	697.6	1395.2	18.3	30.4
137	0.6	202.6	337.6	675.2	1350.4	16.5	24.1
138	0.4	144.2	360.4	720.8	1441.7	24.1	35.9
139	6.5	216.0	332.2	664.5	1329.0	15.0	22.8
140	0.5	174.4	348.8	697.6	1395.2	18.9	30.8

Table C: Testing Data

s/n	W:C Ratio	water (Kg/m^3)	Cement (Kg/m^3)	Fine agg (Kg/m^3	Co agg (Kg/m^3	7day (N/mm^2)	28day(N/mm^2)
1	0.6	202.6	337.6	675.2	1350.4	15.2	22.8
2	0.4	144.2	360.4	720.8	1441.7	24.3	38.0
3	0.5	174.4	348.8	697.6	1395.2	21.1	30.1
4	6.5	216.0	332.2	664.5	1329.0	14.5	22.2
5	6.5	216.0	332.2	664.5	1329.0	14.0	21.7
6	0.5	174.4	348.8	697.6	1395.2	19.5	31.4
7	0.5	174.4	348.8	697.6	1395.2	20.9	32.2
8	6.5	216.0	332.2	664.5	1329.0	15.3	23.0
9	0.4	144.2	360.4	720.8	1441.7	24.3	38.2
10	0.5	174.4	348.8	697.6	1395.2	20.2	31.8
11	0.4	144.2	360.4	720.8	1441.7	25.3	38.8
12	0.4	144.2	360.4	720.8	1441.7	24.7	38.9
13	6.5	216.0	332.2	664.5	1329.0	14.2	22.0
14	0.4	144.2	360.4	720.8	1441.7	26.5	39.1
15	0.6	202.6	337.6	675.2	1350.4	18.2	26.0
16	0.4	144.2	360.4	720.8	1441.7	25.1	38.7
17	6.5	216.0	332.2	664.5	1329.0	13.5	21.3
18	0.5	174.4	348.8	697.6	1395.2	20.8	31.3
19	0.6	202.6	337.6	675.2	1350.4	16.5	24.3
20	0.4	144.2	360.4	720.8	1441.7	24.6	37.9
21	0.4	144.2	360.4	720.8	1441.7	24.9	39.2
22	6.5	216.0	332.2	664.5	1329.0	13.8	21.5
23	0.6	202.6	337.6	675.2	1350.4	17.1	24.7
24	0.5	174.4	348.8	697.6	1395.2	18.0	31.5
25	0.4	144.2	360.4	720.8	1441.7	25.7	38.4
26	0.5	174.4	348.8	697.6	1395.2	18.9	29.9
27	0.5	174.4	348.8	697.6	1395.2	20.6	30.5
28	0.4	144.2	360.4	720.8	1441.7	26.5	39.2
29	0.5	174.4	348.8	697.6	1395.2	21.4	31.1
30	0.4	144.2	360.4	720.8	1441.7	23.5	37.5
31	0.6	202.6	337.6	675.2	1350.4	15.8	23.6
32	0.5	174.4	348.8	697.6	1395.2	20.4	30.4
33	0.5	174.4	348.8	697.6	1395.2	20.2	28.4
34	6.5	216.0	332.2	664.5	1329.0	14.8	22.5
35	0.4	144.2	360.4	720.8	1441.7	26.2	37.8
36	0.5	174.4	348.8	697.6	1395.2	20.7	29.8
37	0.6	202.6	337.6	675.2	1350.4	15.0	22.6
38	6.5	216.0	332.2	664.5	1329.0	13.6	21.3
39	0.6	202.6	337.6	675.2	1350.4	16.0	23.6
40	0.6	202.6	337.6	675.2	1350.4	16.6	24.2
41	0.5	174.4	348.8	697.6	1395.2	18.3	30.3

s/n	W:C Ratio	water (Kg/m^3)	Cement (Kg/m^3)	Fine agg (Kg/m^3	Co agg (Kg/m^3	7day (N/mm^2)	28day(N/mm^2)
42	0.6	202.6	337.6	675.2	1350.4	16.7	24.3
43	6.5	216.0	332.2	664.5	1329.0	15.0	22.8
44	6.5	216.0	332.2	664.5	1329.0	14.1	21.8
45	0.4	144.2	360.4	720.8	1441.7	25.8	36.7
46	0.6	202.6	337.6	675.2	1350.4	15.5	23.1
47	6.5	216.0	332.2	664.5	1329.0	13.8	21.5
48	0.5	174.4	348.8	697.6	1395.2	20.0	30.8
49	6.5	216.0	332.2	664.5	1329.0	14.7	22.5
50	6.5	216.0	332.2	664.5	1329.0	14.3	22.1
51	0.6	202.6	337.6	675.2	1350.4	17.8	25.6
52	0.6	202.6	337.6	675.2	1350.4	17.0	24.8
53	0.4	144.2	360.4	720.8	1441.7	25.0	38.6
54	0.4	144.2	360.4	720.8	1441.7	24.9	38.4
55	0.5	174.4	348.8	697.6	1395.2	20.1	31.4
56	0.6	202.6	337.6	675.2	1350.4	17.0	24.6
57	0.6	202.6	337.6	675.2	1350.4	14.8	22.4
58	6.5	216.0	332.2	664.5	1329.0	14.5	22.3
59	6.5	216.0	332.2	664.5	1329.0	11.7	19.5
60	6.5	216.0	332.2	664.5	1329.0	12.9	20.7