APPLICATION OF NEURAL NETWORK FOR PREDICTING PROPERTIES OF CONCRETE USING BIDA NATURAL GRAVEL AS COARSE AGGREGATE

YUSUF, Abdulazeez

PhD/SEET/2017/1041

FEDERAL UNIVERSITY OF TECHNOLOGY, MINNA, NIGERIA

AUGUST, 2021

ABSTRACT

The production of crushed granite, which is one of the conventional coarse aggregates used in concrete is expensive and energy demanding. This production process leads to the emission of dust particles and also generates noise leading to environmental hazards, which are harmful to humans. But rapid increase in population creates drive towards increase in infrastructural development. This has, in the last decade, overstretched crushed granite in an alarming rate. Many approaches have been used to develop models for predicting the properties of concrete containing various aggregate types. This study is solely focused on applying Artificial Neural Network (ANN) in predicting properties of concrete using Bida Natural Gravel (BNG) as coarse aggregate due to its abundance in the environ. Physical and mechanical properties of the fine and coarse aggregates were determined. Three water-cement ratios (w/c) of 0.40, 0.50 and 0.60. and three coarse aggregate-total aggregate (ca/ta) ratios of 0.55, 0.6 and 0.65 as well as three total aggregate-cement ratios (ta/c) ratios of 3.00, 4.50 and 6.00 was used for factor settings. Full factorial experimental design was used to generate twenty-seven (27) experimental data points. Combinations of constituent materials in each experimental data point were used to produce concrete mixtures. Slump of the concrete were determined and the compressive, flexural, splitting tensile strengths and modulus of elasticity were determined at 28 days curing age. The highest slump of 270 mm was recorded using w/c of 0.60, ca/ta of 0.55 and ta/c of 3.00 while zero slump was recorded using w/c of 0.40, ca/ta of 0.65, 0.6.0 and 0.55 and ta/c ratio of 6.00. Highest compressive, flexural and splitting tensile strengths of 44.30, 7.60 and 3.42 N/mm^2 as well as modulus of elasticity of 32.74 kN/mm^2 was recorded using low w/c ratio of 0.40, medium ratio of 0.55 and low ta/c ratio of 3.00 while the lowest compressive, flexural and splitting tensile strengths of 7.79, 1.60 and 0.57 N/mm^2 respectively and elastic modulus of 4.09 kN/mm^2 was recorded using low w/c ratio of 0.40, medium ca/ta ratio of 0.60 and high ta/c ratio of 6.00. The results obtained were augmented using a MATLAB script and the augmented data sets were used to develop two case ANN models for slump, compressive, flexural, splitting tensile strength and modulus of elasticity using a MATLAB back propagation, feed-forward ANN algorithm. Mean Square Error (MSE), Root Mean Square Error (RMSE) and Regression (R) were used to examine the performance of the models. A 5-89-1 ANN architecture with a tangent sigmoid activation function was found to be sufficient in predicting slump data for concrete using Bida Natural Gravel (BNG) as aggregate. A 5-69-1 ANN architecture with tangent sigmoid activation function was found to be sufficient in predicting compressive strength data, while a 5-91-1 ANN architecture with logistic sigmoid activation function was found to perform best in predicting flexural strength of concrete using BNG as coarse aggregate. Architecture with 5 input neurons, 91 hidden neurons and 1 output neuron (5-91-1) was adjudged to best predict the splitting tensile strength of concrete containing BNG using tangent sigmoid activation function, while a 5-67-1 ANN architecture with a logistic sigmoid activation function was selected for predicting the elastic modulus of concrete containing BNG. The ANN models developed herein can be used in predicting properties of concrete using BNG as coarse aggregate with 98% accuracy.

TABLE OF CONTENTS

CHAPTER TWO

LIST OF TABLES

LIST OF FIGURES

LIST OF APPENDICES

ABBREVIATIONS, GLOSSARIES AND SYMBOLS

ACI	American Concrete Institute
ACV	Aggregate Crushing Value
AD	Air Dry
AIV	Aggregate Impact Value
ANN	Artificial Neural Network
ASTM	American Society for Testing and Materials
BNG	Bida Natural Gravel
BS	British Standard
BS-EN	British Standard European Norm
CA/TA	Coarse Aggregate-Total Aggregate ratio
CEM	Cement
FM	Fineness Modulus
Gc	Specific Gravity of Cement
Gca	Specific Gravity of Coarse Aggregate
Gfa	Specific Gravity of Fine Aggregate
Gw	Specific Gravity of Water
HPC	High Performance Concrete
Kg/cm^3	Kilogramme per Centimeter cube
Kg/m^3	Kilogramme per cubic metre
kHz	Kilohertz
Km^2	Kilometre Square
m^2	Metre Square
MAE	Mean Absolute Error
mm	Millimeter

N/mm^2	Newtons per square of millimetre
Nd	Normalised Data
NN	Neural Network
^{O}C	Degree Centigrade
OD	Oven Dry
OPC	Ordinary Portland Cement
RC	Reinforced Concrete
RHA	Rice Husk Ash
RMSE	Root Mean Square Error
SCMs	Supplementary Cementitious Materials
SF	Silica Fume
SP	Superplasticiser
SSD	Saturated Surface Dry
TA/C	Total Aggregate-Cement ratio
UPV	Ultraviolent Pulse Velocity
Vc	Volume of Cement
Vca	Volume of Coarse Aggregate
Vfa	Volume of Fine Aggregate
Vv	Volume of Air Void
Vw	Volume of Water
w/c	Water-Cement Ratio
Wc	Weight of Cement
Wca	Weight Coarse Aggregate
Wfa	Weight Fine Aggregate
Ww	Weight of Water

CHAPTER ONE

1.0 INTRODUCTION

1.1 Background of the Study

Concrete is no doubt the most flexible and globally used construction material due to its versatility, durability, sustainability and economy when compared to other structural materials. It can be engineered to satisfy a wide range of performance specifications, unlike other building materials, such as natural stone or steel, which generally have to be used as they are. Because the tensile strength of concrete is much lower than its compressive strength, it is typically reinforced with steel bars, in which case it is known as reinforced concrete (Mehta and Monteiro, 1993; Shetty, 2005; Neville, 2011).

The term concrete refers to a mixture of aggregates, usually sand, and either gravel or crushed stone, held together by a binder of cementitious paste. The paste is typically made up of Portland cement and water and may also contain supplementary cementitious materials (SCMs), such as Silica Fume (SF), Fly Ash (FA), Rice Husk Ash (RHA) or slag cement; and chemical admixtures, such as, plasticisers, superplasticiser (SP), and air entraining admixtures (Aitcin, 1998; Nawy, 2008; Caldarone, 2009). Therefore, concrete properties can be enhanced by modifying its properties by the addition of mineral or chemical or both admixtures. Concrete can also be described as a composite material consisting of aggregates enclosed in a matrix of cement paste including possible pozzolans. This implies that concrete has two major components; cement paste and aggregates. The strength of concrete depends on the strength of these components, their deformation properties, and the adhesion between the paste and aggregate surface (Abdullahi, 2009; Neville, 2011; Osama and Sagady, 2013).

Aggregate is a very crucial raw material for preparing concrete, especially coarse aggregate, which greatly affects the concrete performance. Concrete performance, such as, frost resistance, permeability resistance, drying shrinkage, and durability, have been reported to have a direct bearing with aggregate type (Fowler and Quiroga, 2003; Abebe, 2005; Shetty, 2005; Neville, 2011; Yang, 2015). Aggregates can be classified as natural or artificial depending on their sources. Natural aggregates are obtained from quarries by processing crushed rocks or from riverbeds, while artificial aggregates are obtained from industrial by-products, such as, blast furnace slag (Abebe, 2005, Neville, 2011). Natural aggregates are most commonly obtained and are relevant in the Nigerian construction industry, since man-made aggregates are seldom manufactured in the country.

Bida Natural Gravel (BNG), which is the coarse aggregate of interest in this research is a by-product of the Precambrian decomposition, transportation and deposition of rocks of the Bida basin. Bida basin geographically lies in the North central part of Nigeria and is bounded to the North-East and South-West by basement complex (Nuhu, 2009; Alhaji, 2016). The production of BNG involves removal of shrubs, excavation and sieving. The production process is estimated to cost ₦5000 for about 3.8m^3, while the cost of delivery to site is estimated at ₦8,000 compared to conventional crushed granite of the same quantity estimated to cost between ₦65,000 to ₦70,000 excluding cost of delivery to site (Alhaji, 2016). Therefore, BNG is adjudged to be 8 times cheaper than crushed granite. This cost difference has fostered its preponderance in construction in and around Bida basin and environs. Concrete production in areas of similar basement deposits in Nigeria and the world at large may also benefit from the results of this research.

Artificial Neural Network (ANN) refers to a data processing system consisting of a large number of simple, highly interconnected processing elements (artificial neurons) in an architecture inspired by the structure of the central cortex of the human brain. ANN have the ability to learn from experience in order to improve their performance and to adapt themselves to any changes that may arise (Flood and Kartam, 1994a; Mansour *et al.,* 2004; Hola and Schabowicz, 2005). This research is therefore focused on application of artificial neural network for predicting the properties of concrete using BNG as coarse aggregate.

1.2 Problem Statement

The population of Nigeria as at May 2021 is estimated at 210,652,803 people with a population density of 226 people per km^2 (586 people per m^2). The projected population of Nigeria is estimated at 410,637,868 people with a population density of 451 people per km^2 for 2050 (Worldometers, 2021). These will most definitely in the nearest future, lead to a rise in the construction of building and other infrastructure for better living of the Nigerian populace. The chief construction material in Nigeria today is concrete. Conventional crushed granite, which is the main aggregate used in the production of concrete in Nigeria is depleting and also scarce in some parts of Nigeria due to the rapid increase in population (Maneeth and Chandrashekar, 2014; Sulymon *et al.,* 2017). Furthermore, cost of crushed granite is considerably higher than locally sourced gravels. Alhaji (2016) carried out a cost comparative study and reported that Bida Natural Gravel (BNG) is 8 times cheaper than crushed granite. There is therefore the need to explore other coarse aggregate sources for use in concrete production.

Researches carried out by Abdullahi (2012), Olajumoke and Lasisi (2014), Ode and Eluozo (2016), and Sulymon *et al.* (2017) established that the quality of concrete is governed by the type of coarse aggregate used. Coarse aggregate constitutes the largest percentage of the total volume of concrete and its properties greatly affects the strength, durability and general performance of concrete. Therefore, the importance of using the right type and quality of aggregates cannot be overemphasized. Coarse aggregate used in concrete is usually sourced from natural gravel or crushed rock, blast furnace slag, or recycled concrete, ceramics and bricks (Kett, 2000; Alexander and Mindess, 2005; Cachim, 2017; Nawy, 2008; Neville, 2011).

Relationships between constituents of concrete are significant to the response of concrete mixtures. There exist several methods of designing concrete mixtures for modelling purposes. Alhaji (2016), used central composite design for composing concrete mixtures modelled for mechanical properties using natural gravel from Bida environs. Central composite design generally considers reducing the size and complexity of mixture designs, but does not adequately give protection to curvature in the response function (Montgomery, 2001; Tijana *et al.,* 2014; MINITAB, 2017). Furthermore, central composite design may discard useful mixtures relating the interaction of constituents or factors. Without the use of full multilevel factorial experiments, important interactions may remain undetected. Therefore, a full multilevel factorial experiment was used in this study.

Ilyasu (2014) and Shehu *et al. (*2016) used BNG to produce self-compacting concrete measuring properties, such as, the workability, compressive, flexural and tensile strengths. Salihu (2011) also examined the compressive strength of concrete using Bida natural deposit stone, while Alhaji (2016) modeled the mechanical properties of concrete made using coarse aggregate from Bida environs by employing a statistical method. Statistical models generally consider linear, interactive, pure quadratic and full quadratic functions in predicting and modelling properties and parameters in different cases. The process usually consumes time because it involves a lot of trial and error before achieving the best fit model. However, Artificial Neural Network (ANN) models parameters while employing non-linear functions can generate the best model in seconds depending on the volume of data. Information regarding the use of any artificial intelligence technique in predicting properties of concrete made from BNG is scarce in literature. This research is however focused on the application of ANN for predicting strength properties of concrete using BNG.

1.3 Aim and Objectives of the Study

This research is aimed at applying ANN for predicting the strength properties of concrete using Bida natural gravel as coarse aggregate.

To achieve this aim, the objectives are to;

(i) determine the physical and mechanical properties of the constituent materials.

(ii) determine the fresh and hardened properties of the concrete produced using BNG

(iii) develop, train and validate ANN models based on laboratory results.

1.4 Scope and Limitation of the Study

This study was focused on applying ANN for predicting properties of concrete using Bida Natural Gravel (BNG). Bida Natural Gravel (BNG) was selected as the coarse aggregate of choice in this study. The physical and mechanical properties of aggregates determined were limited to those necessary for mix design and those which provides information about the strength of the aggregates; specific gravity, bulk density, moisture content, sieve analysis, water absorption, aggregate impact value as well as aggregate crushing value. The parameters used for mix design were; water-cement ratio (w/c), coarse aggregate-total aggregate ratio (ca/ta) and total aggregate-cement ratio (ta/c). The general multilevel factorial experiment was chosen because it allows for the selection of discontinuous factors and does not discard any combination of factors from the available mixture. This allowed for a true representation of the interrelationship between the constituents of the mixture. The properties of the concrete measured were those which provides information about the workability and strength of the concrete; slump, compressive strength, flexural strength, splitting tensile strength and modulus of elasticity. A three-layer (Input, hidden and output) ANN architecture was used. The ANN model comprised of five (5) input parameters (water-cement ratio, weight of water, weight of cement, weight of fine aggregate and weight of Bida natural gravel). The ANN architecture comprised of five (5) independent output parameters (Slump, compressive strength, flexural strength, tensile splitting strength and elastic modulus). The weights assigned to each neuron in all layers was independently chosen by the model and the back propagation feed forward algorithm was used applying the tansig and logsig activation functions. Many software and algorithms are available for developing artificial neural networks. ANN algorithm embedded in MATLAB (2015) software was used to develop the ANN model.

1.5 Justification of the Study

Due to the progressive increase in population, the demand for affordable housing and sustainable infrastructure will continue to increase. The demand for naturally occurring gravel will therefore continue to increase. The production of crushed granite requires enormous amount of energy and often leads to noise and air pollution. BNG has been reported to be 8 times cheaper than the cost of crushed granite. Furthermore, studies have shown that naturally occurring stones are not prohibited for use in concrete provided that the engineering properties are known and satisfactory. As such, carrying out research to develop an ANN model for predicting the properties of concrete produced using BNG is well justified as the model produced can serve as a tool for researchers in the concrete realm.

The world is gradually embracing artificial intelligent and artificial technology in solving a lot of problems in engineering, medicine, agriculture and other fields. Prediction of the strength properties of concrete has been an active research area over the past two decades. Several research efforts to develop precise models for predicting strength properties of different concrete types using different artificial intelligence techniques are available in literature (Ni and Wang, 2000; Baykasoglu *et al.*, 2004; Akkurt *et al.,* 2004; Oztas *et al*, 2006; Pala *et al.*, 2007; Rajamane *et al.,* 2007; Ozturan *et al.,* 2008; Palika *et al.,* 2008; Alshihri *et al.*, 2009; Saridemir, 2009; Saridemir, 2010; Diab, 2014; Neela *et al.,* 2014; Kirtikanta *et al.*, 2016; Sonebi *et al.*, 2016; Otunyo and Jephter, 2018; El-Khoja *et al.*, 2018; Jin *et al.*, 2019; Marijana *et al.*, 2019). Information regarding the application of ANN to predict strength properties of concrete made using BNG is however rare in literature. This research is therefore justified as the model developed can be used for research purpose and in the field.

CHAPTER TWO

2.0 LITERATURE REVIEW

2.1 Concrete

Concrete is a construction material made up of aggregates (fine and coarse) embedded in a binding agent such as, a combination of Portland cement and water. Many researchers have noted that concrete is the most widely consumed construction material in today's world (Mehta and Monteiro, 1993; Abebe, 2005; Crow, 2008; Nishant, 2016), but the type of aggregates and other constituents differ from region to region due to their availability and structural application of the resulting concrete.

2.1.1 Types of concrete

Concrete used in construction all over the world has been distinguished and classified according to different criteria. Types of concrete used in construction and their properties contained in Zongjin (2011) are presented below:

(a) Normal Strength Concrete: The concrete that is obtained by mixing the basic ingredients cement, water and aggregate will give us normal strength concrete. The strength of these type of concrete will vary from 10 N/mm^2 to 40 N/mm^2. The normal strength concrete has an initial setting time of 30 to 90 minutes that is dependent on the cement properties and weather conditions of the construction site

(b) Plain Concrete: The plain concrete will have no reinforcement in it. The main constituents are the cement, aggregates, and water. Most commonly used mix design is 1:2:4, which is the normal mix design. The density of the plain concrete will vary between 2200 and 2500 kg/m^3. the compressive strength is between 200 to 500 kg/cm^3. These types of concrete are used in the construction of pavements and building especially in area where there is less demand for high tensile strength.

(c) Reinforced Concrete: Reinforced Concrete (RCC) is defined as the concrete to which reinforcement is introduced to bear the tensile strength. Plain concrete is weak in tension and good in compression. Hence, the placement of reinforcement will take up the responsibility of bearing the tensile stresses. RC works with the combined action of the plain concrete and the reinforcement. The steel reinforcement used in the concrete can be in the form of rods, bars or in the form of meshes. Now fibers are also developed as reinforcement. Fiber reinforced concrete are concrete that use fibers (steel fibers) as reinforcement for the concrete. The use of meshes in concrete will give ferrocement. Whatever be the type of reinforcement used in concrete, it is very necessary to ensure proper bond between the concrete and the reinforcement. This bond will control the strength and durability factors of the concrete.

(d) Prestressed Concrete: Most of the mega concrete projects are carried out through prestressed concrete units. This is a special technique in which the bars or the tendons used in the concrete is stressed before the actual service load application. During the mixing and placing of the concrete, these tensioned bars are placed firmly and held from each end of the structural unit. Once the concrete sets and hardens, the structural unit will be put in compression. This phenomenon of prestressing makes the lower section of the concrete member to be stronger against the tension. The process of prestressing will require heavy equipment and labour skill (jacks and equipment for tensioning). Hence, the prestressing units are made at site and assembled at the construction site. These are used in the application of bridges, heavy loaded structures, and roof with longer spans.

(e) Precast Concrete: Various structural elements can be made and cast in the factory as per the specifications and brought to the site at the time of assembly. Such concrete units are called as the precast concrete. The examples of precast concrete units are concrete blocks, staircase units, precast walls and poles, concrete lintels and many other elements. These units have the advantage of acquiring speedy construction as only assemblage is necessary. As the manufacturing is done at site, quality is assured. The only precaution taken is for their transportation.

(f) Lightweight Concrete: Concretes that have a density lesser than 1920 kg/m^3 will be categorized as lightweight concrete. The use of lightweight aggregates in concrete design give lightweight aggregates. Aggregates are the important element that contributes to the density of the concrete. The examples of light weight aggregates are the pumice, perlites, and scoria. The light weight concrete is applied for the protection of the steel structures and are also used for the construction of long span bridge decks. These are also used for the construction of the building blocks.

(g) High-Density Concrete: The concretes that have densities ranging between 3000 to 4000 kg/m^3 which are made using heavy weight aggregates are called heavyweight concrete. The crushed rocks are used as the coarse aggregates. The most commonly used heavy weight aggregates is Barytes. These types of aggregates are most commonly used in the construction of atomic power plants and for similar projects. The heavy weight aggregate helps the structure to resist all possible types of radiations.

(h) Air Entrained Concrete: There are concrete types into which air is intentionally entrained for an amount of 3 to 6% of the concrete. The air entrainment in the concrete is achieved by the addition of foams or gas – foaming agents. Some examples of air entraining agents are resins, alcohols, and fatty acids.

(i) Ready Mix Concrete: The concrete mixed and bathed in a central mixing plant is called ready-mix concrete. The mixed concrete is brought to the site with the help of a truck-mounted transit mixer. This once reached in the site can be used directly without any further treatment. The ready-mix concrete is very precise and specialty concrete can be developed based on the specification with utmost quality. The manufacture of these concrete will require a centralized mixing plant. These plants will be located at an adjustable distance from the construction site. If the transportation is too long then it will result in setting of concrete. Such issues of time delay are adjusted to the use retarding agents that delays the setting.

(j) Polymer Concrete: When compared with the conventional concrete, in polymer concrete the aggregates are bound with the polymer instead of cement. The production of polymer concrete helps in the reduction of volume of voids in the aggregate. This thus reduce the amount of polymer that is necessary to bind the aggregates used. Hence, the aggregates are graded and mixed accordingly to achieve minimum voids which result into maximum density. This type of concrete has different categories: Polymer Impregnated Concrete, Polymer cement concrete and Partially Impregnated concrete.

(k) High-Strength Concrete: The concretes that have strength greater than 40 N/mm^2 can be termed as high strength concrete. This increased strength is achieved by decreasing the water-cement ratio even lower than 0.35. The calcium hydroxide crystals that are the major concerned product during hydration for the strength properties is reduced by the incorporation of silica fume. In terms of performance, the high strength concrete ought to be less performing in terms of workability which is an issue.

(l) High-Performance Concrete: These concretes conform to a particular standard but in no case, is limited to strength. It has to be noted that all the high strength concrete can be high-performance type. But not all high-performance concrete (HPC) is high strength concrete. Standards that conform to the high-performance concrete are enlisted below:

i. Strength gain in early age
ii. Easy placement of the concrete
iii. Permeability and density factors
iv. Heat of hydration
v. Long life and durability
vi. Toughness and life term mechanical properties
vii. Environmental concerns

(m) Self – Consolidated Concrete: The concrete mix when placed compacts by its own weight and it is regarded as self-consolidated concrete. No vibration must be provided for the same separately. This mix has a higher workability. The slump value will be between 650 and 750mm. This concrete due to its higher workability is also called as flowing concrete. The areas where there is thick reinforcement, self – consolidating concrete works best.

(n) Shotcrete Concrete: Here the concrete type differs in the way it is applied on the area to be cast. The concrete is shot into the frame or the prepared structural formwork with the help of a nozzle. As the shooting is carried out in a higher air pressure, the placing and the compaction process will be occurring at the same time.

(o) Pervious Concrete: Pervious or permeable concrete are concrete that are designed in such a way that it allows water to pass through it. These types of concrete will have 15 to 20% voids of the volume of the concrete when they are designed. The pervious concrete is created by a unique mixing process, performance, application methods. These are used in the construction of pavements and driveways where storm water issues persist. The storm water will pass through these pervious concrete pavements and reach the groundwater. Hence, most of the drainage issues is solved.

(p) Vacuum Concrete: Concrete with water content more than required quantity is poured into the formwork. The excess water is then removed out with the help of a vacuum pump without waiting for the concrete to undergo setting. Hence, the concrete structure or the platform will be ready to use earlier when compared with normal construction technique. These concretes will attain their 28 days compressive strength within a period of 10 days and the crushing strength of these structure is 25 % greater compared with the conventional concrete types.

(q) Pumped Concrete: One of the main properties of the concrete used in large mega construction especially for high-rise construction is the conveyance of the concrete to heights. Hence one such property of concrete to easily pump will result in the design of pumpable concrete. The concrete that is used for pumping must be of adequate workability so that it is easily conveyed through the pipe. The pipe used will be rigid or a flexible hose that will discharge the concrete to the desired area. The concrete used must be fluid in nature with enough fine material as well as water to fill up the voids. The more the finer material used, greater will be the control achieved on the mix. The grading of the coarse aggregate used must be continuous in nature.

(r) Stamped Concrete: Stamped concrete is an architectural concrete where realistic patterns similar to natural stones, granites, and tiles can be obtained by placing impression of professional stamping pads. These stamping is carried out on the concrete when it is in its plastic condition. Different coloring stains and texture work will finally give a finish that is very similar to much expensive natural stones. A high aesthetic look can be obtained from a stamped finish economically. This is used in the construction of driveways, interior floors, and patios.

(s) Limecrete: This is a concrete type in which the cement is replaced by lime. The main application of this product is in floors, domes as well as vaults. These unlike cements have many environmental and health benefits. These products are renewable and easily cleaned.

(t) Asphalt Concrete: Asphalt concrete is a composite material, mixture of aggregates and asphalts commonly used to surface roads, parking lots, airports, as well as the core of embankment dams. Asphalt concrete is also called as asphalt, blacktop or pavement in North America, and tarmac or bitumen macadam or rolled asphalt in the United Kingdom and the Republic of Ireland.

(u) Roller Compacted Concrete: These are concrete that is placed and compacted with the help of earth moving equipment like heavy rollers. This concrete is mainly employed in the excavation and filling needs. These concretes have cement content in lesser amount and filled for the area necessary. After compaction, these concretes provide high density and finally cures into a strong monolithic block.

(v) Rapid Strength Concrete: As the name implies these concretes acquires strength within few hours after its manufacture. Hence the formwork removal is made easy and thus, the building construction is covered as fast as possible. These have a wide spread application in the road repairs as they can be reused after few hours.

(w) Glass Concrete: Recycled glass can be used as aggregates in concrete. Thus, we get a concrete of modern times, the glass concrete. This concrete increases the aesthetic appeal of the concrete. They also provide long-term strength and better thermal insulation. Properties of concrete are influenced by many factors mainly due to mix proportion of cement, sand, aggregates and water.

2.2 Constituent of Concrete

2.2.1 Portland cement

Many cement classes and types exist in the market today. These cements have distinct characteristics owing to adjustment in their constituent materials to meet certain performance target. The cements used in the production of concrete possess the ability to set and harden in the presence of water and are termed hydraulic cements. Hydraulic cements can be categorised as natural cements, Portland cements, and high-alumina cements (Neville, 2011; Mehta and Montero, 2001; Aitcin, 1998). The majority of buildings and other concrete-based infrastructure in Nigeria are constructed using Portland cement. Various types of Portland cement have been specified for different applications. The governing factors for the choice of Portland cement include; construction type, chemical composition of the soil, the cost of construction and the construction pace. Five types of Portland cement are (Neville, 2011);

(i). Type I Portland cement: Type I cements are utilised for general and normal constructions. They are used for pavement constructions where concrete is not susceptible to sulphate attacks or where hydration does not result to excessive fluctuation.

(ii). Type II Portland cement. Type II cements are modified and generates lesser heat at a slower rate than Type I, but possess an enhanced resistance to sulphate. They are applicable in hot weather when moderate heat generation tends to minimize the rise in temperature.

(iii). Type III Portland cement. Type III cements are employed in cases where high early strength is desirable in construction. Formworks can be disconnected early and the concrete can be put in service as soon as possible. It is also used to reduce the amount of time uncured cement is exposed to low temperatures. High strength can suitably and cost effectively be achieved at the early stages with Type III cements than with Type I.

(iv). Type IV Portland cement. Type IV cements are necessary when the quantity and rate of heat liberated must be kept at a minimum. Its strength development is much slower than Type I cements. Type IV is normally used in large, mass projects, such as, concrete dams, to combat the rise in temperature where heat generated during hardening may be a critical factor, for the strength development of the resulting concrete when placed.

(v). Type V, Sulfate-resistant Portland cement. Type V cement is used in structures that are exposed to severe sulfate action, such as, areas that have water with a high acid content. It gains strength at a slower rate than Type I.

The widely utilised type of Portland cement in Africa and particularly in Nigeria today is Ordinary Portland Cement (OPC), which by ASTM C150 – 97 (2000) classification falls under Type I cement. According to BS EN 197-1 (2011), common cements are grouped into five CEM classes depending on the percentage of clinker, major as well as minor additives. Portland cement is however, a product obtained after blending and crushing a combination of limestone and clay or shale together, and heating the resulting mixture to 1450^{o}C in a rotary kiln to produce clinker (Zongjin, 2011 and Neville, 2011). The clinker produced is pulverised and further processed with gypsum to produce a greyish powder called Portland cement. This ultimately implies that the basic ingredients used for the production of Portland cement are limestone, clay, iron ore and some amount of gypsum. Cement in any concrete should develop strength as it hydrates over time and also possess excellent rheology in the fresh state (Shah and Ahmad, 1994; Neville, 2011; Zongjin, 2011). Normal strength concretes usually contain cement in the range of 300 – 450 kg/m^3 but in high strength and high-performance concrete (HPC), the amount of cement in addition to other supplementary cementitious materials (SCM) is between 500 – 650 kg/m^3 (Shah and Ahmad, 1994; Neville and Aitcin, 1998).

2.2.2 Water

Concrete is usually made with hydraulic cements. Cements are chemical compounds that set or harden in the presence of water. It is therefore necessary to prepare concrete with the purest water to hydrate cement and lubricate the aggregates to enhance workability. Nearly all natural, odourless and tasteless water that is safe for drinking can be used as mixing water for concrete making (Nawy, 2008; Neville, 2011). BS 3148 (1980) stipulates that water possessing harmful constituents, contaminants, silt, sugar, oil and other forms of chemicals is damaging to the strength and setting times of cement. Although ASTM C94 (2021) opined that water that is not safe for drinking may be used to make concrete provided that it satisfies some acceptance criteria. The primary factor governing the selection of water for use in concrete is related to the performance in the wet and solid state. Impurities in water have an adverse effect on the strength and setting times of cement as well as the durability of the resulting concrete since chemical constituents present in water may actively participate in the chemical reactions and thus affect the setting, hardening and strength development of concrete (Nawy, 2008; Kucche *et al.,* 2015). Sources of water applicable for concrete production are categorized into three: added water, inherent aggregate moisture and liquid addictive in form of plasticisers and superplasticisers (Abdullahi, 2009; Aitcin, 1998; Shetty, 2005). Health issues regarding handling of water used in concrete production is also of great concern. Therefore, the suitability of water can be identified from past service records or tested to performance limits, such as, setting times, compressive strength and durability test. Limits are specified for mixing water with their constituents, such as, total alkalis and chloride sulfate. Biological treatment and pathogen reductions are also required to ensure safety in handling of reclaimed water and saline water (Neville, 2011).

2.2.3 Aggregates

Globally, aggregates are recognised to be fragments of rocks or its equivalent which can be used in its bounded or unbounded form to construct a part or total building or infrastructure. Aggregates accounts for 65-75% of overall concrete volume and are important ingredients in concrete production (Abebe, 2005; Nawy, 2008; Neville, 2011). In other words, about three-quarters of the total volume of concrete are made up of aggregates. Hence, the quality and type of aggregate is of significant importance when producing concrete of any grade, because properties of aggregates have a direct relationship with the strength and durability of the resulting concrete. The cost of aggregates is cheaper than cement. It is, therefore, necessary to incorporate into a concrete mix as much aggregates as possible in other to produce a cost-effective concrete. Aggregates also offer a great technical benefit in concrete. They give higher volume stability and excellent durability when compared to cement paste only. The size of aggregates used in concrete ranges from tens of millimetres down to particles less than one-tenth of a millimetre in cross-section. The maximum size actually varies but, in any mix, particles of different sizes are incorporated, the particle size distribution being referred to as grading (Neville, 2011; Neville and Brooks, 2001). Aggregates used in concrete can either be natural, artificial or recycled aggregate. Natural mineral aggregates include sand, gravel or crushed rocks derived from natural sources. Artificial aggregates can be thermally processed materials like expanded clays and shale or aggregates manufactured from industrial by-products like fly-ash and blast furnace slag. Recycled aggregates on the other hand are obtained from municipal and recycled concrete from demolished buildings and pavements (Neela *et al*, 2014; Kamran, 2015; Kirtikanta *et al,* 2016). To produce good quality concrete however, aggregates in at least two size groups are used. The aggregates not larger than 4 mm in size termed as fine aggregate and referred to as sand in BS EN 12620 (2008) as well as those termed as coarse aggregates comprising of materials greater than 5mm in size (Nawy, 2008; Neville, 2011). Therefore, aggregates in concrete are of two types, fine aggregate (sand) and coarse aggregate (crushed stone or gravel).

(a). Fine aggregate

Research carried out to ascertain the optimum properties of fine aggregates sufficient for use in concrete is scarce in literature owing to the fact that the characteristics of fine aggregates can be extensive particularly from one region to another (Mack and Leistikow, 1996). Fine aggregates used to produce normal strength concrete usually possess a particle size distribution within the range recommended by ACI -221R (1996). Nonetheless, the selected fine aggregates to be used in concrete should fall on the coarse side of these limits, which stipulates a fineness modulus of 2.7 to 3.0 (Aitcin 1998; Neville and Aitcin 1998). The use of coarse sand results in a slight decrease in the amount of mixing water necessary for a given workability, which is advantageous from a strength and economic point of view. Finally, the use of a coarse sand results in an easier shearing of the cement paste during mixing (Aitcin, 1998). Generally, there is no particular advantage to using one type of sand rather than another as long as it is clean and free from clay and silt.

(b). Coarse aggregates

Selecting coarse aggregates for concrete is more crucial than selecting fine aggregate as the target compressive strength of concrete increases. In most cases, water-cememt ratio is the factor that governs the strength of concrete, but studies have shown that strength of coarse aggregates as well plays an important role in the strength of concrete (Aginam, 2013; Kaplan, 1959; Cordon and Gillespie, 1963; Ezeldin and Aitcin, 1991; Rocco and Elices, 2009; Abdullahi, 2012). Coarse aggregates account for about 75% of concrete by volume. Therefore, its properties cannot be neglected. Crushed limestone, dolomite as well as igneous rocks such as granite, diorite, gabbro, syenite and diabase of plutonic origin have been successfully used to produce concrete. The sharpness and angularity of coarse aggregates measures the roundness of the aggregates which is controlled by the strength and abrasion resistance of the parent rock (Neville, 2011). Classification of roundness is well documented in BS 812 - 1 (1975) and recently revised and published as BS EN 933-4 (2008) and it is presented in Table 2.2. Natural mineral aggregates constitute the most essential class of aggregates for Portland cement concrete production (Mehta and Montero, 2001). Nearly 70% of concrete produced in Nigeria today are made up crushed rock. Natural mineral gravel takes the remaining 30%. Many researchers have sort alternative aggregate other than crushed granite for concrete production in Nigeria. Natural mineral aggregates are obtained from various rock types, which are made up of several minerals (Omar, 2009).

Natural and bush gravel have proven to be a viable alternative to crushed granite and they have been used in the production of concrete particularly in Nigeria and different regions of the world. Maneeth and Chandrashekar (2014) used river stone obtained from India as coarse aggregates in concrete. In the same vein, Zahid *et al*. (2015) used natural aggregates from Kashmir province in India for the production of concrete. In Nigeria however, Apebo *et al.* (2013) carried out a comparative study on concrete made from aggregates obtained from river Benue; Ezeokonkwo *et al.* (2015) prepared concrete for compressive strength using natural aggregates form Anambra, South-East Nigeria; Aginam *et al.* (2013) also investigated the impact of various natural coarse aggregates from South-East Nigeria on the compressive strength of concrete. Olajumoke and Lasisi (2014) examined the strength of concrete made with dug-up gravel existing in Ile-Ife area of South-West Nigeria, while Sulyman *et al.* (2017) and Fakuyi *et al.* (2019) reported the use of natural gravel for concrete in South-West Nigeria. Ode and Eluozo (2016), found out that impurities in gravel impacts the compressive strength of concrete prepared with unwashed gravel occurring in South-South Nigeria. Bamibgoye *et al.* (2016) also explored the possibility of using gravel from South-South Nigeria. All of these researches confirmed that natural gravels can be used for preparing concrete of various grades. Efforts have been made to characterize the properties of BNG and examine its suitability for concrete production. Ilyasu (2014) and Shehu *et al.* (2016) used BNG in the production of self-compacting concrete, while Salihu (2011), Alhaji (2016) and Yusuf *et al.* (2020) used BNG for the production of normal strength concrete. These researches confirmed that BNG can be used in place of conventional crushed granite in concrete preparation.

Bida Natural Gravel (BNG) is a by-product of the Precambrian decomposition, transportation and deposition of rocks of the Bida basin. Bida Basin is assumed to be a northwesterly extension of the Anambra Basin (Akande *et al.,* 2005; Nuhu, 2009). The basin fill comprises a north west trending belt of Upper Cretaceous sedimentary rocks that were deposited as a result of block faulting, basement fragmentation, subsidence, rifting and drifting consequent to the cretaceous opening of the South Atlantic Ocean (Nuhu, 2009).

Table 2.1: Particle size classification of aggregates

Classification	Description	Examples
Rounded	Fully water-worn of completely shaped by attrition	River or seashore gravel; desert, seashore and wind-blown sand
Irregular	Natural irregular, or partly shaped by attrition and having rounded edges	Other gravels; land or dug flint

Flaky	Material of which the thickness is small relative to the other two dimensions	laminated rock
Angular	Possessing well-defined edges formed at the intersection of roughly planar phases	Crushed rock of all types; talus; crushed slag
Elongated	Material, usually angular, in which the length is considerably larger than the other two dimensions	-
Flaky and Elongated	Material having the length considerably larger than the width, and the width considerably larger than the thickness	-

Source: BS EN 933-4 (2008)

(c). Properties of aggregates and their significance

(i). Particle shape and texture of aggregates

The shape and texture of fine and coarse aggregates have a direct bearing on the workability of the resulting concrete and to some extent the strength. Essentially, to reduce the quantity of cement paste sufficient to provide required workability of fresh concrete, aggregates with roughly equidimensional shape with relatively smooth surfaces are desirable (Aitcin, 1998; Metha and Montero, 2001, Neville, 2011). These properties are peculiar to most natural sands and gravels. Where natural sand and gravel are unavailable, crushed stone may be used. Crushed stone tends to have a rougher surface and to be more angular in shape. As a result, it tends to require rather more cement paste for workability. Whether using natural gravels or crushed stone, however, either flat or elongated particles should be avoided, as they will lead to workability and finishing problems (Abdullahi, 2012; Shetty, 2005).

(ii). Aggregate water absorption and moisture content

Aggregates can possess water by absorbing it within the aggregate porosity or by holding it as a moisture film on the particle surface. For mix design reasons, it is important to be aware of the quantity of water the aggregate can absorb from the mixing water or the amount of water the aggregate can supply to the mix. Aggregates moisture condition can therefore be defined in four ways (Neville, 2011; Shetty, 2005);

(a) Oven Dry (OD): This condition is obtained by keeping the aggregate in an oven at a temperature of 110°C long enough to drive all water out from internal pores and, hence, reach a constant weight.

(b) Air Dry (AD): This condition is obtained by keeping the aggregate at ambient temperature and ambient humidity. Under such condition, pores inside of aggregate are partly filled with water. When the aggregate is under either the OD or AD condition, it will absorb water during the concrete mixing process until the internal pores are fully filled with water.

(c) Saturated Surface Dry (SSD): In this situation, the pores of the aggregates are fully filled with water and the surface is dry. This condition can be obtained by immersing coarse aggregates in water for 24 h followed by drying of the surface with a wet cloth. When the aggregate is under the SSD condition, it will neither absorb water nor give out water during the mixing process. Hence, it is a balanced condition and is used as the standard index for concrete mix design.

(d) Wet (W): The pores of the aggregate are fully filled with water and the surface of the aggregate has a film of water. When aggregate is in a wet condition, it will give out water to the concrete mix during the mixing process. Since sand is usually obtained from a river, it is usually in a wet condition.

The absorption capacity, effective absorption, and surface moisture data are invariably needed for correcting the batch water and aggregate proportions in concrete mixtures made from stock materials. As a first approximation, the absorption capacity of an aggregate, which is easily determined, can be used as a measure of porosity and strength. Normally, moisture correction values for intrusive igneous rocks and dense sedimentary rocks are very low, but they can be quite high in the case of porous sedimentary rocks, lightweight aggregates, and damp sands. Typically, the effective absorption values of trap rock, porous sandstone, and expanded shale aggregates are 1/2, 5, and 10 percent respectively.

iii. Density and apparent specific gravity

For the purpose of proportioning concrete mixtures, it is not necessary to determine the true specific gravity of an aggregate. Natural aggregates are porous; porosity values up to 2 percent are common for intrusive igneous rocks, up to 5 percent for dense sedimentary rocks, and 10 to 40 percent for very porous sandstones and limestones. For the purpose of mix proportioning, it is desired to know the space occupied by the aggregate particles, inclusive of the pores existing within the particles. Therefore, determination of the apparent specific gravity, which is defined as the density of the material including the internal pores, is sufficient. The apparent specific gravity for many commonly used rocks ranges between 2.6 and 2.7; typical values for granite, sandstone, and dense limestone are 2.69, 2.65, and 2.60, respectively. For mix proportioning, in addition to the apparent specific gravity, data are usually needed on bulk density, which is defined as the weight of the aggregate fragments that would fill a unit volume. The phenomenon of bulk density arises, because it is not possible to pack aggregate fragments together, such that there is no void space. The term bulk is used since the volume is occupied by both aggregates with voids. The approximate bulk density of aggregates commonly used in normal-weight concrete ranges from 1300 to 1750 kg/m^3.

d. Unit weight

The unit weight is defined as the weight per unit bulk volume for bulk aggregates. In addition to the pores inside each single aggregate, the bulk volume also includes the space among the particles. According to the weight measured at different conditions, the unit weight can be divided into UW (SSD) and UW (OD):

e. Crushing strength, abrasion resistance and elastic modulus

Crushing strength, abrasion resistance, and elastic modulus of aggregates are interrelated properties, which are greatly influenced by porosity. Aggregates from natural sources that are commonly used for making normal weight concretes are generally dense and strong, and therefore are seldom a limiting factor to strength and dynamic elastic modulus for most granites, basalts, trap rocks, flints, quartzitic sandstone, and dense limestones are in the range 210 - 310 N/mm^2 and 70 - 90 N/mm^2, respectively. But with regard to sedimentary rocks, the porosity varies over a wide range, and so will their crushing strength and related characteristics. In one investigation involving 241 limestones and 79 sandstones, while the maximum crushing strengths for each rock type were of the order of 240 N/mm^2, some limestone and sandstones showed as low as 96 N/mm^2 and 7000 48 N/mm^2 crushing strengths, respectively.

f. Particle grading

The particle-size distribution in a sample of aggregate, referred to as the grading, is generally expressed in terms of the cumulative percentage of particles passing (or retained on) a specific series of sieves. These distributions are most commonly shown graphically as grading curves. In practice, one can provide good concrete with quite a range of aggregate grading. Although the continuous type of grading is the most common, other types of grading are sometimes used for special purposes; for example, gap grading refers to a grading in which one or more of the intermediate size fractions is omitted. This is sometimes convenient when it is necessary to blend different aggregates to achieve a suitable grading. Such concretes are also prone to segregation of the fresh concrete. No-fines concrete is a special case of gap-graded concrete in which the fine aggregate (< 4.75 mm) is omitted entirely to produce a porous, lighter weight concrete that, for example, may allow water to drain through it. For fine aggregates, the particle-size distribution tends to be described by a single number, the fineness modulus (FM).

2.2.4 Admixtures

Historically, admixtures are almost as old as concrete itself. The Romans used milk, animal fat, and blood to improve the properties of concrete (Zongjin, 2011). Although these were added to improve workability, blood was a very effective air-entraining agent and might well have improved Roman concrete durability. In more recent times, calcium chloride was often used to accelerate the hydration of cement. The systematic study of admixtures began with the introduction of air-entraining agents in the 1930s (Zongjin, 2011), when it was accidentally found that cement ground with beef tallow (grinding aid) had more resistance to freezing and thawing than a cement ground without beef tallow. The concrete properties, both in fresh and hardened states, can be modified or improved by admixtures. The benefits of admixtures to concrete are listed in Table 2.3. Today, almost all the contemporary concretes contain one or more admixtures. It is thus important for practitioners to be familiar with commonly used admixtures (Zongjin, 2011). Admixtures are chemicals or minerals, added to concrete, mortar or grout at the time of mixing, to enhance the properties, either in the wet state, immediately after mixing or after the mix has hardened (Newman and Choo, 2003). They can be a single chemical or a blend of several chemicals and may be in powdered form, but most are aqueous solutions because in this form they are easier to accurately dispense into, and then disperse through the concrete. The active chemical is typically 35 - 40% in liquid admixtures but can be as high as 100% (shrinkage-reducing admixtures) and as low as 2% (synthetic air-entraining admixtures).

Table 2.2: Beneficial effects of different kinds of admixtures on concrete properties

Concrete Properties	Admixture Type	Category of Admixture
Workability	Water reducers	Chemical
	Air-entraining agents	Air entraining
	Inert mineral powder	Mineral
	Pozzolans	Mineral
	Polymer latexes	Miscellaneous
Set control	Set accelerators	Chemical
	Set retarders	Chemical
Strength	Pozzolans	Mineral
	Polymer latexes	Miscellaneous
Durability	Air-entraining agents	Air entraining
	Pozzolans	Mineral
	Water reducers	Chemical

Source: Zongjin (2011)

2.3 Properties of Concrete

Fresh properties of concrete as well as the mechanical properties of the hardened concrete are very important parameters that defines the grade and quality of concrete. Major properties of concrete are discussed briefly:

2.3.1 Concrete in its fresh state

Fresh concrete is the nomenclature given to rheological concrete having a well-defined plasticity. Plastic concrete gives room for transportation, placing, compaction and surface finishing. It is therefore of paramount necessity to study fresh concrete properties as it considerably affects the strength of a particular concrete mix. The properties of fresh concrete which influence maximum compaction include; consistency, mobility and compactibility. In concrete technology, these three properties are referred to as the workability of the concrete (Gambhir, 2001; Nawy, 2008; Neville and Brooks, 2001; Naville, 2011; Zongjin, 2011). Tests commonly required to measure workability are slump, compacting factor and V-B consistometer test. Slump test is the most commonly used measure of workability and it is prescribed in BS 1881 - 102 (1983). Three types of slump can be observed during slump test as shown in Figure 2.1;

i. True slump

This type of slump is observed with cohesive and rich mixes for which the slump is generally sensitive to variation in workability.

ii. Shear slump

Shear slump occurs more often in leaner mixes than harsh mixes. Whenever shear slump is obtained, the test should be repeated and, if persistent, this fact should be recorded together with test result.

iii. Collapse slump

This is usually associated with very wet mixes and is generally indicative of poor quality concrete and most frequently result from segregation of its constituents materials. The standard slump apparatus is only suitable for concretes in which the maximum aggregate size does not exceed 37.5mm (Jackson, 1980; Gambhir, 2001).

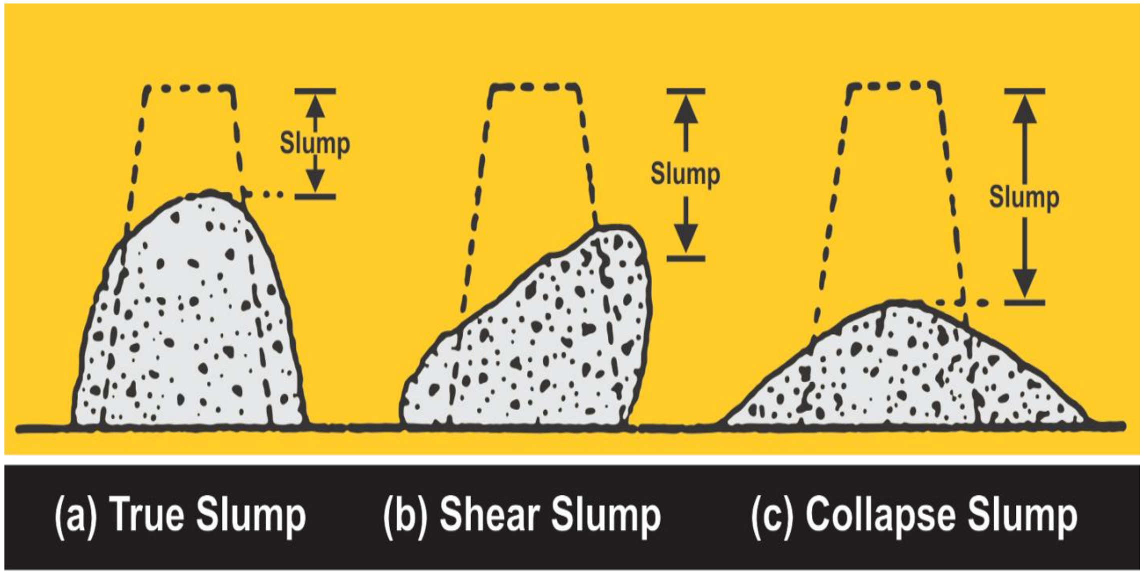


Figure 2.1: Types of Concrete Slump (Yusuf *et al.,* 2020)

2.3.2 Hardened concrete

Concrete must be proportioned and produced to carry live or imposed loads, resist deterioration, deformations and be dimensionally stable. The quality of concrete is characterised by its mechanical properties and ability to resist deterioration. The mechanical properties of concrete can broadly be classified as short-term and long-term properties. Short-term properties include strength in compression, tension, bond and modulus of elasticity. The long-term properties include creep, shrinkage, behaviour under fatigue and durability characteristics, such as, porosity, permeability, freeze-thaw resistance and abrasion resistance (Zia *et al*, 1991; Gambhir, 2001; Neville, 2011).

2.3.2.1 Compressive strength

Concrete compressive strength is widely used in specifying, controlling and evaluating concrete quality. The strength of concrete depends on a number of factors including the properties and proportioning of the constituent materials, degree of hydration, rate of loading, method of testing and specimen geometry. The maximum compressive strength that can be achieved practically have increased steadily in the last decade. Presently, 28 days strengths of up to 84 N/mm^2 are routinely obtainable (Shetty, 2005; Aitcin, 1998). For various strengths of concrete, compressive strength is the property generally specified in construction design and quality control. The reasons are as follows:

(a) It is relatively easy to measure.
(b) It is believed that other properties can be related to the compressive strength and can be deduced from strength data.

The 28-day compressive strength of concrete, determined by a standard uniaxial compression test, is accepted universally as a general concrete property index for structural design. To measure different strengths of concrete, various tests have to be conducted with a universal testing machine (Neville, 2011; Zongjin, 2011).

2.3.2.2 Flexural strength

Flexural strength also called the modulus of rupture, can be determined by performing four-point bending test following the procedures of ASTM C78 (2021) or BS 1881-118 (1983). The specimen for a flexural strength test is a 150 × 150 × 500 mm beam according to ASTM C78 (2021), and a 150 × 150 × 750 mm beam according to BS 1881-118 (1983). The British Standard (BS) also allows a beam size of 100 × 100 × 500mm when the maximum size of aggregate is less than 25 mm. According to the mechanics of materials, it is believed that under the four-point bending, the middle third portion of the beam is under pure bending.

2.3.2.3 Tensile strength

The tensile strength governs the cracking behaviour and affects other properties such as stiffness, damping action, bond to embedded steel and durability of concrete. It is also of importance with regard to the behaviour of concrete under shear loads. The tensile strength is determined either by direct tensile tests or by indirect tensile tests such as flexural or split cylinder tests (ACI 363, 2010). Uniaxial tension test is more difficult to conduct for three reasons. First, it is difficult to center the loading axis with the mechanical centroid. Second, it is difficult to control the loading process due to the quasi-brittle nature of concrete under tension. Third, the tension process is more sensitive to a sudden change in cross-sectional area, and the specimen-holding devices introduce secondary stresses that cannot be ignored. The indirect tension test is also called the splitting test or Brazilian test. The standard specimen for the splitting test is a 150 × 300-mm cylinder (BS 1881 - 117 (1983); ASTM C496-71 (2004)). It should be prepared by filling concrete into the mould in three equal layers, with each layer being stroked 35 times by a hemispherical-tipped steel rod. The curing requirement is the same for the compression specimen. The splitting test is carried out by applying compression loads along two axial lines that are diametrically opposite. The loading rate is 0.02 to 0.04 $N/mm^2/sec$ according to BS 1881 – 177 (1983), and 0.011 to 0.023 $N/mm^2/sec$ according to ASTM C496-71 (2004). Under such a line load, the stress along the central diameter will be distributed.

2.3.2.4 Bond

Bond strength is defined as the shear strength between the aggregate, fiber, reinforcing steel, and cement paste. The bond strength plays an important role in determining the properties of concrete, fiber reinforced concrete, and reinforced concrete. There is considerable evidence to indicate that the interface is the weakest region in concrete. In general, bond failure occurs before failure of either the paste or aggregate. Many researchers have tried to measure the bond properties and have developed many models to interpret the experimental results. Two types of bond strength are of interest in concrete application; bond strength of concrete-to-concrete and bond strength of reinforced steel. Bond strength between paste and reinforcement is proportional to the tensile strength of concrete. It is therefore a function of compressive strength: the higher the compressive strength, the higher the bond strength. The strength of concrete is derived from the bond between paste and aggregate (Shetty, 2005; Abdullahi, 2009; Neville, 2011). This bond strength depends upon the surface texture of the aggregate, mineralogical nature of the aggregate and the specific surface of the gel. The inherent micro-cracks that are generated within the body of the concrete also influence the bond strength between paste and aggregate.

2.3.2.5 Deformation

The deformation of concrete depends on short term properties, such as, static and dynamic modulus, as well as strain capacity. It is also affected by time dependent properties, such as, shrinkage and creep. The modulus of elasticity is generally related to the compressive strength of concrete. This relationship depends on the aggregate type, mix proportions, curing conditions, rate of loading and method of measurement. More information is available on the static modulus than on the dynamic modulus, since the measurement of elastic modulus can be routinely performed, whereas the measurement of dynamic modulus is relatively more complex (Shetty, 2005).

2.3.2.6 Poisson's ratio

Poisson's ratio under uniaxial loading condition is defined as the ratio of lateral strain to strain in the direction of loading. In the elastic range, due to volume dilation resulting from internal micro-cracking, the apparent Poisson's ratio is not constant but is an increasing function of the axial strain. Piosson's ratio tends to increase with decreasing water-binder ratio. Using dynamic measurements, it was found that values of poisson's of concrete ranged from 0.23 to 0.32 regardless of compressive strength, coarse aggregate and test age for 17 to 79 N/mm^2 concretes (ACI 363, 2010).

2.3.2.7 Shrinkage

Shrinkage is the decrease in the volume of concrete with time. This decrease is as a result of the change in moisture content and physiochemical properties, which occur without stress attributable to actions external to the concrete. Swelling is the increase of concrete volume with time. Shrinkage and swelling are usually expressed as a dimensionless strain under given condition of relative humidity and temperature. Drying shrinkage is considerably less in high performance concrete due to lower water-binder ratio (Aitcin, 1998, Neville, 2011).

2.4 Mix Design of Concrete

It can be said that the properties of concrete are studied primarily for the purpose of selection of appropriate mix ingredients. In the British usage, the selection of the mix ingredients and their proportions is referred to as mix design. This term, although common, has the disadvantage of implying that the selection is a part of the structural design process. The American term mixture proportioning is unexceptional, but it is not used on a world-wide basis. Although structural design is not normally concerned with mix selection, the design imposes two criteria for this selection: strength of concrete and its durability. It is important to add an implied requirement to the effect that workability must be appropriate for the placing conditions. The workability requirement applies not only to, say, slump at the time of discharge from the mixer, but also to a limitation on the slump loss, up to the time of placing of concrete. Because of the dependence of the required workability upon the site conditions, workability should generally not be fixed prior to the consideration of the construction procedure.

In addition, the selection of mix proportions has to take into account the method of transporting the concrete, especially if pumping is envisaged. Other important criteria are: setting time, extent of bleeding, and ease of finishing; these three are interlinked. Considerable difficulties can arise, if these criteria are not properly taken into account during the selection of the mix proportions or when adjusting these proportions. The selection of mix proportions is thus, simply, the process of choosing suitable ingredients of concrete and determining their relative quantities with the object of producing as economically as possible concrete of certain minimum properties, notably strength, durability, and required consistency.

The British approach, contained in BS EN 206-1 (2006) and the complementary BS 8500-2 (2015), recognise four methods of specifying concrete mixes. A designed mix is specified by the designer principally in terms of strength, cement content, and water/cement ratio; compliance relies on strength testing. A prescribed mix is specified by the designer in terms of the nature and proportions of mix ingredients; the concrete producer simply makes the concrete ‘to order’. The assessment of mix proportions is used for compliance purposes, strength testing not being routinely used. The use of prescribed mixes is advantageous when particular properties of concrete, for instance, with respect to its finish or abrasion resistance, are required. However, a prescribed mix should be specified only when there are sound reasons for assuming that it will have the required workability, strength, and durability. A standardized mix is based on ingredients and proportions fully listed in BS 5328-2 (2002) for several values of compressive strength up to 25 N/mm^2, measured on cubes. The fourth and last type of mix is the designated mix, for which the concrete producer selects the water/cement ratio and the minimum cement content, using a Table of structural applications coupled with standard mixes. This approach can be used only if the concrete producer holds a special certificate of product conformity based on product testing and surveillance, coupled with certification of quality assurance. Standard mixes are used only in minor construction, such as, housing. Designated mixes, although they can be used for strengths up to 50 N/mm^2, are limited in application to routine construction. It is, therefore, only in the selection of designed and prescribed mixes that a full knowledge of properties of concrete can be used. These four types of mixes are varied in BS 8500-2 (2015). In the American practice, when there is no experience on the basis of which mix proportions could be selected and trial mixes made, it is necessary to base the mix proportions on standard proportions which, in order to be safe, are perforce very stringent. This approach can be used only for low strength concrete.

The current British method of mix selection is that of the Department of the Environment revised in 1997. Similarly, to the ACI 211 (2001) approach, the British method explicitly recognizes the durability requirements in the mix selection. The method is applicable to normal weight concrete made with Portland cement only or also incorporating ground granulated blast furnace slag or fly-ash, but it does not cover flowing concrete or pumped concrete; nor does it deal with lightweight aggregate concrete. Three maximum sizes of aggregate are recognized: 40, 20, and 10 mm. In essence, the British method consists of 5steps, as follows.

Step 1. This deals with compressive strength for the purpose of determining the water/cement ratio. The concept of target mean strength is introduced, this being equal to the specified characteristic strength plus a margin to allow for variability. The target mean strength is thus similar in concept to the mean compressive strength of ACI 318 R-05 (2005). The relation between strength of concrete and the water/cement ratio is dealt with rather ingeniously. Certain strengths are assumed at a water/cement ratio of 0.5 for different cements and types of aggregates. The latter factor recognizes the significant influence of aggregates on strength.

Step 2. This deals with the determination of the water content for the required workability, expressed either as slump or as Vebe time, recognizing the influence of the maximum size of aggregate and its type, namely crushed or uncrushed. It can be noted that the compacting factor is not used in mix selection, although it can be used for control purposes.

Step 3. This determines the cement content, which is simply the water content divided by the water/cement ratio. This cement content must not conflict with any minimum value specified for reasons of durability or maximum value specified for reasons of heat development.

Step 4. This deals with the determination of the total aggregate content. This requires an estimate of the fresh density of fully compacted concrete, which can be read off for the appropriate water content (from Step 2) and specific gravity of the aggregate. If this is unknown, the value of 2.6 for uncrushed aggregate and 2.7 for crushed aggregate can be assumed. The aggregate content is obtained by subtracting from the fresh density the value of the cement content and of the water content.

Step 5. This determines the proportion of fine aggregate in the total aggregate, using the recommended values of only data for 20 and 40mm aggregates are shown. The governing factors are: the maximum size of aggregate, the level of workability, the water/cement ratio, and the percentage of fine aggregate passing the 600 µm sieve. Other aspects of the grading of the fine aggregate are ignored and so is the grading of the coarse aggregate. Once the proportion of fine aggregate has been obtained, multiplying it by the total aggregate content gives the content of fine aggregate.

2.5 Artificial Neural Network

The concept of neural networks was originally introduced by Donald Hebb in the early 1950's after studying how neurons in the brain adapt to learning and postulating a simple training technique known as the Hebb's law (Hebb, 1949). In 1958, Rosenblatt expanded the scope of Hebb by developing a mathematical model based on the perception training algorithm (Hajela and Berke, 1991). Further research carried out in the early 1980's resulted in the development of efficient, speedy, simple and alternative modelling using back propagation algorithms (Caudill and Butler, 1990). This gave engineers enough confidence to explore neural networks as a modelling tool. Artificial Neural Networks (ANN) are computational models inspired by the nervous system of living beings. They have the ability to acquire and maintain knowledge (information based) and can be defined as a set of processing units, represented by artificial neurons, interlinked by a lot of interconnections (artificial synapses), implemented by vectors and matrices of synaptic weights. The most relevant features concerning artificial neural applications are the following:

(a) Adapting from experience;

The internal parameters of the network, usually its synaptic weights, are adjusted with the examination of successive examples (patterns, samples, or measurements) related to the process behavior, thus enabling the acquisition of knowledge by experience.

(b) Learning capability;

Through the usage of a learning method, the network can extract the existing relationship between the several variables of the application.

(c) Generalization capability;

Once the learning process is completed, the network can generalize the acquired knowledge, enabling the estimation of solutions so far unknown.

(d) Data organization;

Based on innate information of a particular process, the network can organise this information, therefore enabling the clustering of patterns with common characteristics.

(e) Fault tolerance;

Thanks to the high number of interconnections between artificial neurons, the neural network becomes a fault-tolerant system, if part of its internal structure is corrupted to some degree.

(f) Distributed storage;

The knowledge about the behavior of a particular process learned by a neural network is stored in each one of the several synapses between the artificial neurons, therefore improving the architecture robustness in the case where some of the neurons are lost.

(g) Facilitated prototyping;

Depending on the application particularities, most neural architectures can be easily prototyped on hardware or software, since its results, after the training process, are usually obtained with some fundamental mathematical operations.

The information processing performed by the human brain is carried out by biological processing components, operating in parallel, for producing proper functions, such as, thinking and learning. The fundamental cell of the central nervous system is the neuron, and its role comes down to conduct impulses (electrical stimuli originated from physical–chemical reactions) under certain operation conditions. This biological component can be divided into three main parts: dendrites, cell body (also known as "soma"), and axon. Dendrites are composed of several thin extensions that form the dendritic tree (Figure 2.2). The fundamental purpose of dendrites is to acquire, continuously, stimuli from several other neurons (connectors) or from the external environment, which is the case of some neurons in contact with the environment (also called sensory neurons). The cell body is responsible for processing all the information that comes from the dendrites, to produce an activation potential that indicates if the neuron can trigger an electric impulse along its axon. It is also in the cell body where the main cytoplasmic organelles (nucleus, mitochondria, centriole, lysosome, and so forth) of the neuron can be found. The axon is composed of a single extension whose mission is to guide the electrical impulses to other connecting neurons, or to neurons directly connected to the muscular tissue (efferent neurons). The axon termination is also composed of branches called synaptic terminals. The synapses are the connections, which enable the transfer of electric axon impulses from a particular neuron to dendrites of other neurons, as illustrated in Figure 2.2. It is important to note that there is no physical contact between the neurons forming the synaptic junction, so the neurotransmitter elements released on the junction are in charge of weighting the transmission from one neuron to another.

In fact, the functionality of a neuron is dependable of its synaptic weighting, which is also dynamic and dependent on the cerebral chemistry (Hodkin and Huxley, 1952). In short, although the activities related to the biological neuron might seem very simple at first, its components, when functioning altogether, are responsible for all the processing executed and managed by the human brain. It is estimated that this biological neural network, with very eccentric features, is composed of about 100 billion (1011) neurons. Each one of those is interconnected through synaptic connections (made possible by more than fifty neurotransmitter substances) to an average of 6,000 neurons, thus resulting in a total of 600 trillion synapses (Hodkin and Huxley, 1952).

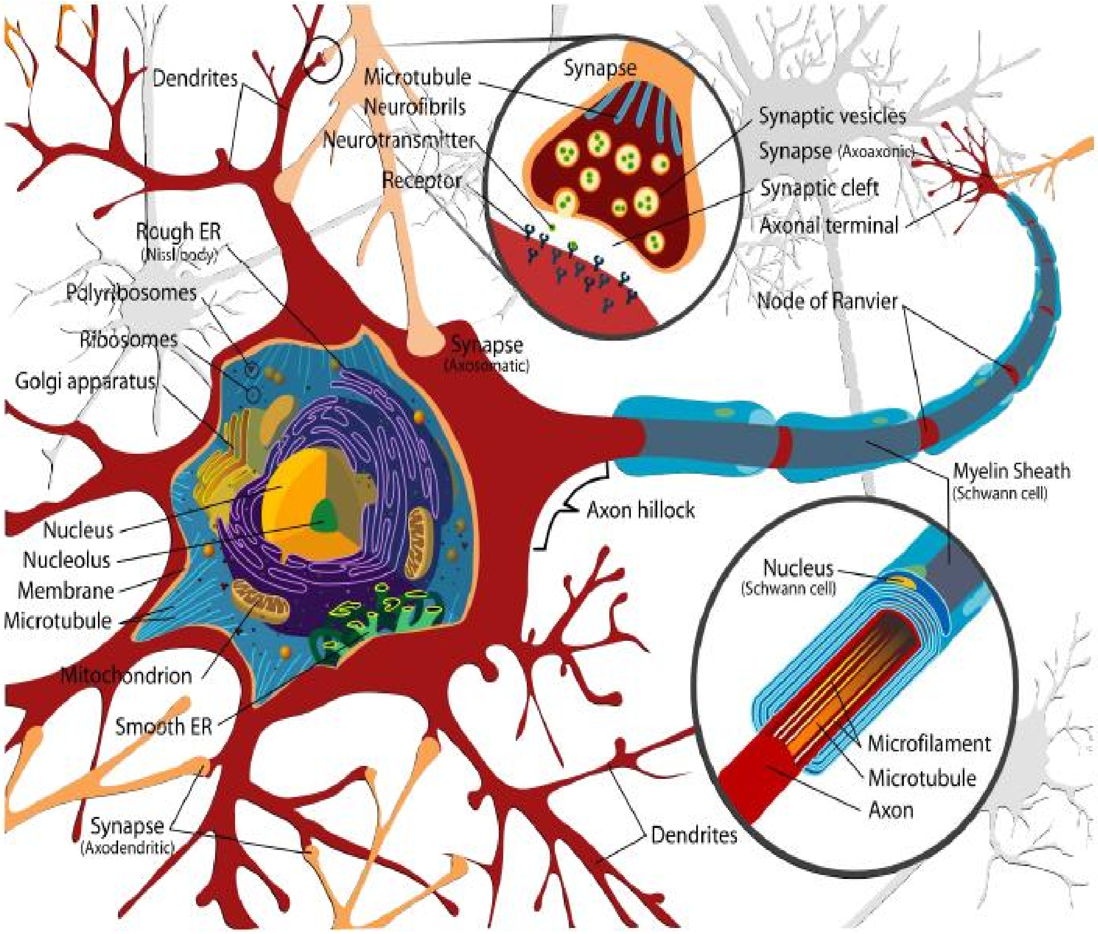


Figure 2.2: Structure of biological neuron (Hodkin and Huxley, 1952)

2.5.1 Artificial neuron

The artificial neural network structures were developed from known models of biological nervous systems and the human brain itself. The computational components or processing units, called artificial neurons, are simplified models of biological neurons. These models were inspired by the analysis of how a cell membrane of a neuron generates and propagates electrical impulses (Hodgkin and Huxley, 1952). The artificial neurons used in artificial neural networks are nonlinear, usually providing continuous outputs, and performing simple functions, such as, gathering signals available on their inputs, assembling them according to their operational functions, and producing a response considering their innate activation functions. The simplest neuron model that includes the main features of a biological neural network—parallelism and high connectivity—was proposed by McCulloch and Pitts (1943), and is still the most used model in different artificial neural network architectures.

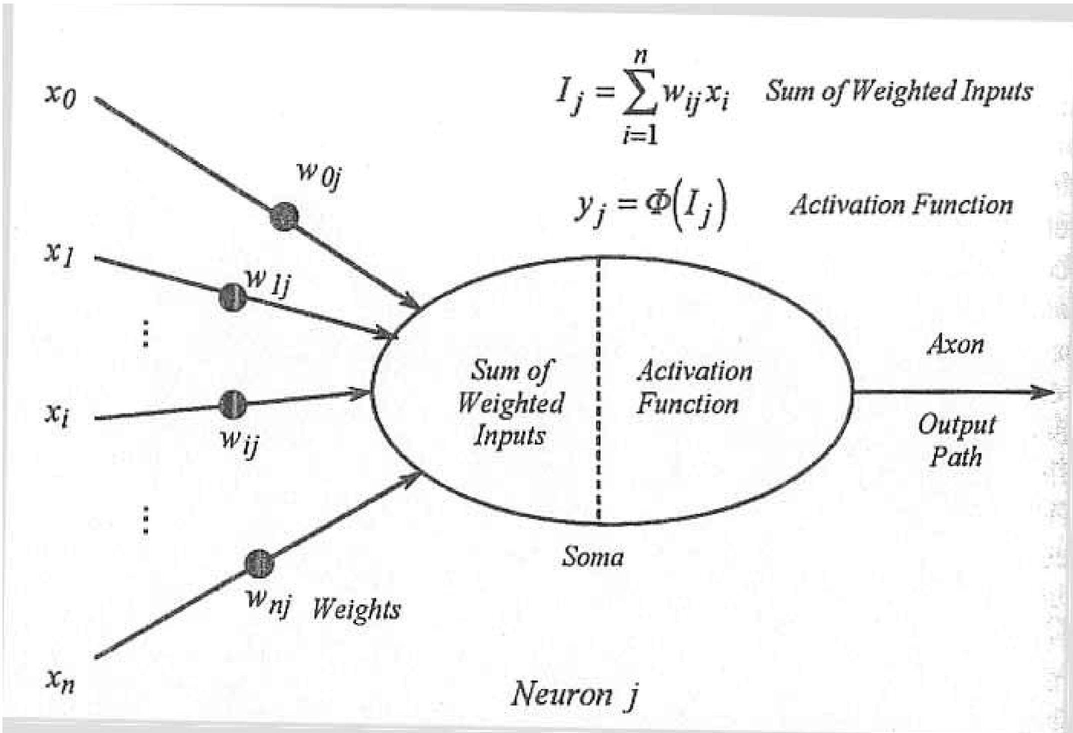


Figure 2.3: Structure of artificial neuron (McCulloch and Pitts, 1943)

In that model, each neuron from a network can be implemented as shown in Figure 2.3 The multiple input signals coming from the external environment (application) are represented by the set $\{x_1, x_2, x_3, \ldots, x_n\}$, analogous to the external electrical impulses gathered by the dendrites in the biological neuron. The weighing carried out by the synaptic junctions of the network are implemented on the artificial neuron as a set of synaptic weights $\{w_1, w_2, \ldots, w_n\}$. Analogously, the relevance of each of the $\{x_i\}$ neuron inputs is calculated by multiplying them by their corresponding synaptic weight $\{w_i\}$, thus weighting all the external information arriving to the neuron. Therefore, it is possible to verify that the output of the artificial cellular body, denoted by u, is the weighted sum of its inputs.

Artificial neural network is a network of simple elements called neurons that receives input signals, change their internal state (activation) according to that input and produce output depending on the input and activation (Mohammed *et al.,* 2013). A neural-network structure is a collection of parallel processors connected together in the form of a directed graph, organized such that the network structure lends itself to the problem being considered (Stuart and Peter, 2010). A typical network diagram is shown in Figure 2.4; each processing element (or unit) is schematically represented in the network as a node, with connections between units indicated by the arcs. The direction of information flow in the network is indicated through the use of the arrowheads on the connections (Stuart and Peter, 2010).

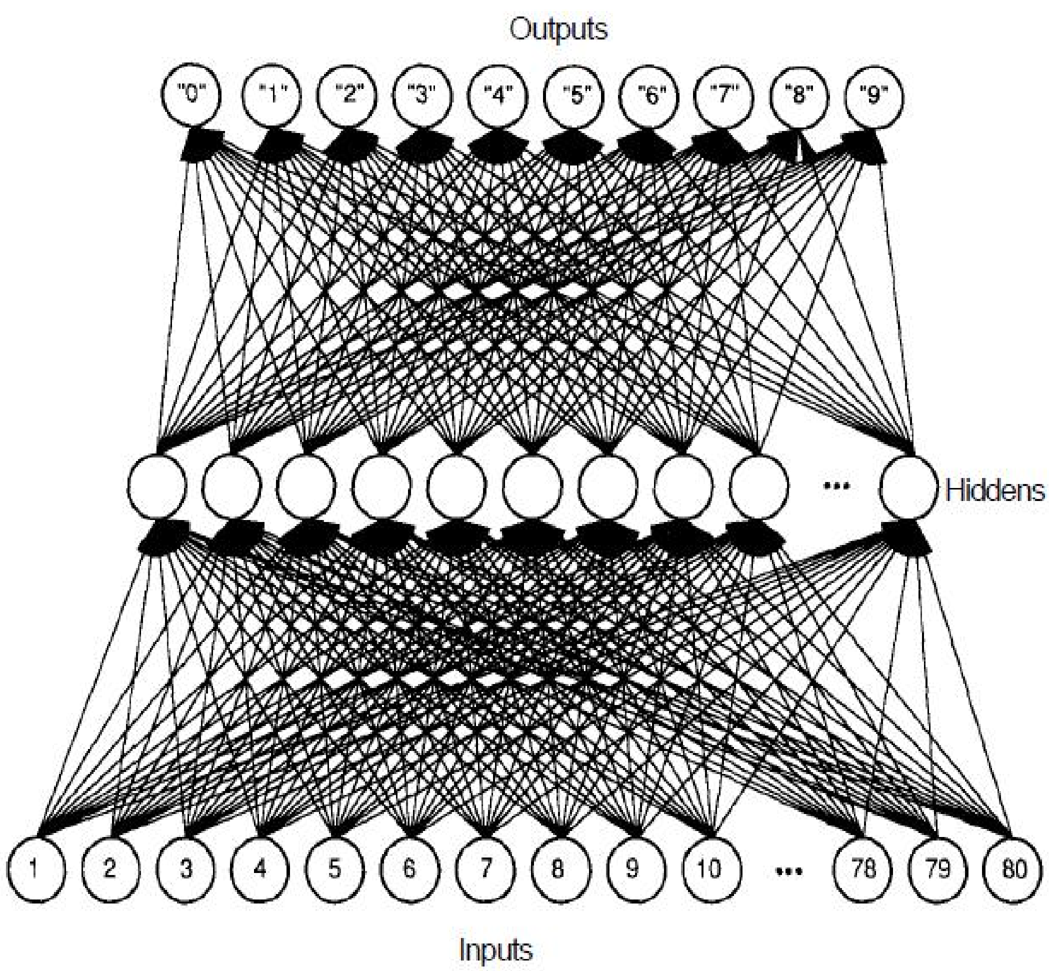


Figure 2.4: A typical network diagram (Stuart and Peter, 2010)

Artificial neural network is a typical example of a modern interdisciplinary subject that helps in solving a wide range of engineering problems which could not be solved by the statistical method and traditional modelling. Neural networks are capable of collecting, memorizing, analysing and processing considerable collections of data gained from some experiments, survey or numerical analyses. They are an illustration of sophisticated modelling technique that can be used for solving many complex and emerging problems. The trained neural network serves as an analytical tool for qualified predictions of the results, for any input data, which were not included in the learning process of the network. The operation is reasonably simple and easy, nonetheless correct and precise. Using the concept of the artificial neural networks and the results of the performed numerical analyses as input parameters, the prediction model for defining the fire resistance of reinforced concrete columns incorporated in walls and exposed to standard fire from one side, has been made (Marijana *et al.,* 2019).

2.5.2 Artificial neural networks – basic concepts

The artificial neural networks, together with the fuzzy logic and genetic algorithms, belong to the group of symbolic methods of intelligent calculations and data processing that operate according to the principles of soft computing. Neural networks are developed as a result of the positive features of a few different research directions: data processing, neuro-biology and physics. They are a typical example of one modern interdisciplinary field, which gives the basic knowledge principles that are used for solving many different and complex engineering problems that could not be solved otherwise (using the traditional modelling and statistical methods) (Marijana *et al.,* 2019). The inspiration for foundation, development and application of artificial neural networks came out of the attempt of understanding the work of human brain and from the aspiration of creating an artificial "intelligent" system for data calculation and processing that are typical for the homo-sapiens brain. As a result, the artificial neural networks are very similar to the biological neural networks. Both networks have similar structure, function, and technique of data processing and methodology of calculation. Artificial neural networks are presented as a simplified mathematical model, a model that is similar and analogous to the biological neural networks. They can easily simulate the basic characteristics of the biological nervous system. The networks are capable of gathering, memorizing and processing numerous experimental data. Some of their basic characteristics are the following: they can analyse large number of data, they can learn from the past data and they can solve problems that are complex, not clear and problems that do not have a unique solution. Because of that, the artificial neural networks are often a classic and traditional calculation methods (Marijana *et al.,* 2019).

Research made around the world showed that neural networks have an excellent success in prediction of data series and that is why they can be used for creating prognostic models that could solve different problems and tasks.

2.5.3 Neuron

Processes inside the biological neural networks are very complex and they still cannot be completely studied and explained. There are hundreds of different types of biological neurons in human brain, so it is almost impossible to create a mathematical model that will be absolutely the same as the biological neural network. However, for practical application of artificial neural networks, it is not necessary to use complex neuron models. Therefore, the developed models for artificial neurons only remind one of the structures of the biological ones and they have no pretension to copy their real condition (Marijana *et al.,* 2019).

2.5.4 Neural network

Neural network is composed of numerous mutually connected neurons grouped in layers. The complicity of the network is determinate by the number of layers. Beside the input (first) and the output (last) layer, the network can have one or few hidden layers. The purpose of the input layer is to accept data from the surroundings. Those data are processed in the hidden layers and sent into the output layer. The final results from the network are the outputs of the neurons from the last network layer and that is actually the solution for the analysed problem. The input data can have any form or type. The basic rule is that for each data, there must be only one input value. Depending on the problem's type, the network can have one or few outputs as showed in Figure 2.5.

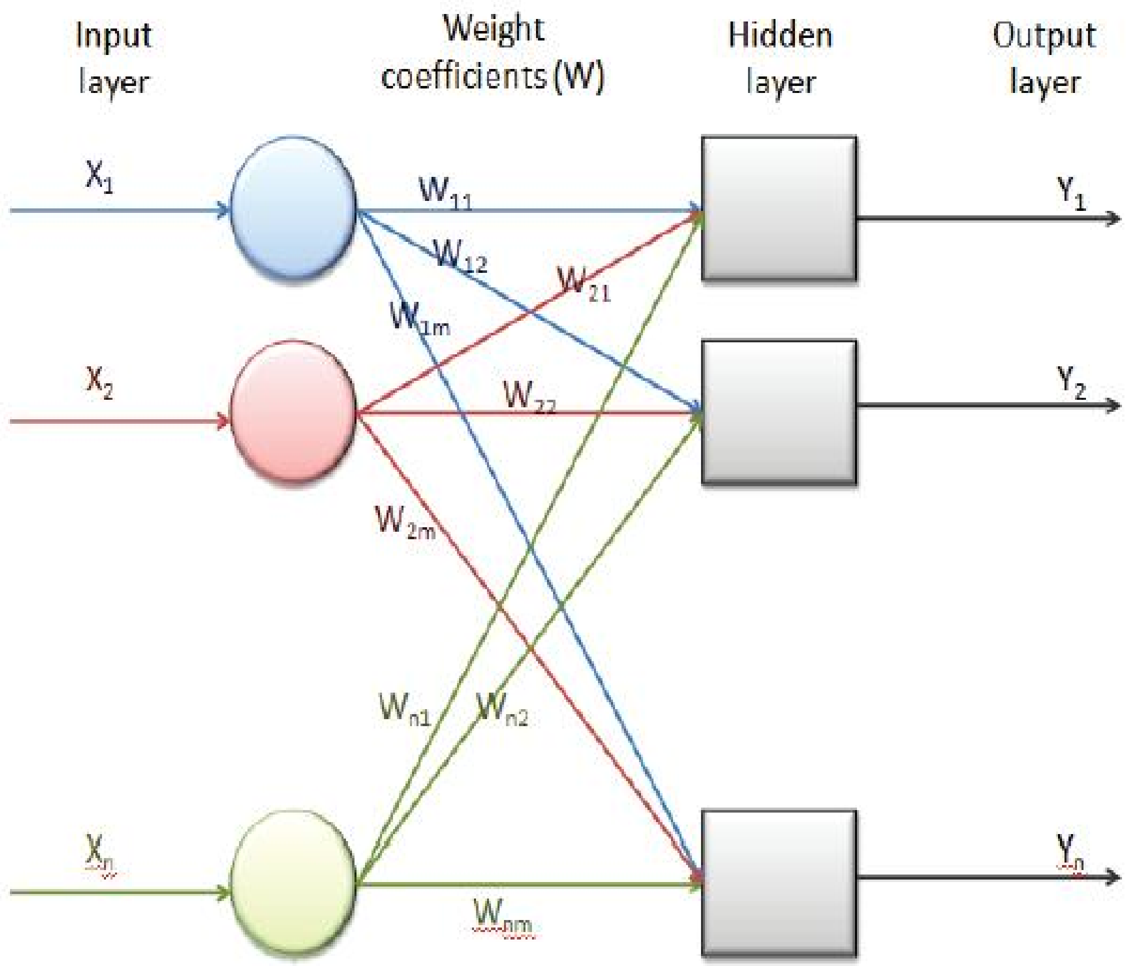


Figure 2.5: Model of one layered artificial neural network (Marijana *et al.,* 2019)

2.5.5 Weight coefficients

Weight coefficients are the primary elements of every neural network. They express the relative importance of each neuron's input and determine the input's capability for stimulation of the neurons. Every input neuron has its own weight coefficient. By multiplying those weight coefficients with the input signals and by summing that, the input signal from each neuron is calculated. In Figure 2.5, the input data are marked as X_1, X_2 and X_3, and the appropriate weight coefficients are W_1, W_2 and W_3. The input neuron impulses are W_1X_1, W_2X_2 and W_3X_3. Neuron registers the summed input impulse which is equal to the sum of all input impulses: $X = W_1X_1 + W_2X_2 + W_3X_3$. The received impulse is processed through an appropriate transformation function (activation function), $f(x)$, and the output signal from the neuron will be: $Y = f(x) = f(W_1X_1 + W_2X_2 + W_3X_3)$ (Marijana *et al.,* 2019). Weight coefficients are elements of the matrix W that has n rows and m columns. For instance, the weight coefficient Wnm is actually the mth output of the nth neuron (Figure 2.5). The connection between the signal's source and neurons is determined by the weight coefficients. Positive weight coefficient means speeding synapse and negative coefficient means inhibiting synapse. If $Wij = 0$ it means that there is no connection between these two neurons. One very important characteristic of neural networks is their ability for weight adjustment according to the received history data, which is actually the learning process of the network (Marijana, *et al.,* 2019).

2.5.6 Activation function

The main purpose of the activation (transformation) function is to determine whether the result from the summary impulse $X = W_1X_1 + W_2X_2 +.... + WnXm$ can generate an output. This function is associated with the neurons from the hidden layers and it is mostly a recognised non-linear function. Almost every non-linear function can be used as an activation function, but the common practice is to use the sigmoid function (hyperbolic tangent and logistic) with the following form: $Y_t = \frac{1}{(1+e^{-y})}$.

where: Y_t is normalised value of the result of the summary function. The normalisation means that the output's value, after the transformation, will be in reasonable limits, between 0 and 1 (Marijana *et al*., 2019). If there is no activation function and no transformation, the output value might be too large, especially for complex networks that have few hidden layers.

2.5.7 Architecture of neural networks

A very vital aspect of neural networks is how to link the network elements. There are many different models of neural networks and many different ways for their classification (Marijana *et al.,* 2019). Generally speaking, types of networks are divided according to: number of layers (one layered and multi-layered networks), connection type between neurons (layered, fully connected and cellular), learning process (feed forward and feedback), data type (binary and continuous networks), course of information spreading (supervised, partly supervised and unsupervised networks), and a host of others.

2.5.8 The training process

ANN have several basic characteristics, among which their learning capability takes an important place (this capability brings them closer to the real world and human thinking), together with their capability of discovering connection between chaotic and incomprehensible data and their generalizing capability (the network will give quality outputs even though the input data are not completed). In many cases it is shown that the neural networks are a better calculation method compared to the classic methods, mostly because of their capability to analyse data that contain errors, or to solve problems that have no reasonable solution and to learn from the past data. The training (learning) process of neural networks consists of periodic data transmission through the network and compartment of the received input values with the expected ones. If there is a difference between those values, then a weight coefficient's adjustment (modification of the neuron connections) has to be made. This process is repeated a few times until the network reacts in the correct manner, or until all the weight coefficients from all the training data are being adjusted. When the network gives correct outputs for all of the training data, it can be said that it is a trained network. After the training process the network should be able to generate outputs for new input data different from the training ones (Marijana *et al.,* 2019). The learning and training process that occurs inside neural networks is of huge importance for their applicability in solving engineering problems.

2.6 Application of Neural Network in Civil Engineering

Habeeb (2000) studied the effect of high temperatures (up to 800°C) on some mechanical properties of high strength concrete. Three design strength investigated were 40, 60 and 80 N/mm^2. The investigated properties were compressive strength, volume changes and flexural strength. Ultrasonic pulse velocity (U.P.V) and dynamic modulus of elasticity were tested as well. The specimens were heated slowly to five temperature levels (100, 300, 500, 600 and 800 °C), and to three exposure periods 1.0, 2.0 and 4.0 hours without any imposed loads during heating. The specimens were then cooled slowly and tested either one day or one month after heating. He concluded that the HSC is more sensitive to high temperatures than normal strength concrete. The residual compressive strength ranged between (90 - 106 %) at 100 °C, (72 - 103 %) at 300°C, (55 - 87 %) at 500°C and (22 - 66 %) between (600 - 800°C). The author concluded that exposure time beyond one hour had a significant effect on the residual compressive strength of concrete; however, the effect was diminished as the level of temperature increased. Moreover, the compressive strength at age of one month after heating, suffered an additional loss than at age of one day after heating. The flexural strength was found to be more sensitive to high temperature exposure than compressive strength the residual flexural strength was in the range of (92 - 98 %), (52 - 98 %) and (29-47 %) at 100, 300, and 500 °C respectively and (2 - 30%) at (600 - 800) °C. The author also noticed that the U.P.V and Ed were more sensitive to elevated temperature on exposure than compressive strength.

Husem (2006) examined the variation in compressive and flexural strengths of ordinary and high-performance concretes exposed to high temperatures of 200, 400, 600, 800 and 1000°C and then cooled in air or water. The compressive and flexural strengths of these concrete specimens were compared with each other and with unheated specimens. On the other hand, strength loss curves of these concrete specimens were compared with the strength loss curves given in the codes. In this study, ordinary concrete with an average compressive strength of 34 N/mm^2 and high-performance concrete with an average compressive strength of 71 N/mm^2 were produced. From the results obtained, it was concluded that

(a) For ordinary and high-performance concrete exposed to high temperature, the flexural and compressive strengths decrease with the increase in temperature. Such decrease is greater when the specimens were cooled in water.

(b) The compressive strength of high-performance concrete cooled in air and water decreases up to 200°C and increases between 200 and 400°C. The compressive strength gain was 13% for the specimens cooled in air and 5% for those cooled in water. The compressive strength of ordinary concrete decreases continuously.

(c) The compression test was not done on ordinary concrete at temperatures above 600°C, because the concrete specimens disintegrated. For high- performance concrete, the compression test was not done at temperatures above 800°C.

(d) The concrete may completely lose its strength as a result of the immediate expansions that take place during the expansion of mineral admixture used in the production of high- performance concretes at high temperature.

(e) It was observed that some high-performance concrete specimens spalled explosively at temperatures between 400 and 500°C, which is attributed to expansion of silica fume used in the production of such concretes. Explosive spalling was not observed for ordinary concrete specimens.

(f) Experimental studies indicated that ordinary and high-performance concretes produced using limestone aggregate underwent high percentages of strength loss in the specimens cooled in water after high temperature exposure.

(g) The CEN Eurocode and the CEB design curves for the properties of fire-exposed concrete are not applicable to high strength concrete. The Finnish Code is more suitable especially up to 400°C. These codes are not applicable to ordinary and high-performance concrete cooled in water.

Yeh (2006), Lee (2003) and Ahmet *et al*. (2006) applied the ANN for predicting properties of conventional concrete and high-performance concrete. Kim *et al*. (2004) used back propagation neural networks to predict the compressive strength of ready mixed concrete. Hola and Schabowicz (2005) developed ANN models to predict the compressive strength of concrete on the base of non-destructive determined parameters. Zarandi *et al.* (2008) applied the fuzzy polynomial neural network to predict the compressive strength of concrete.

Boukhatem *et al.* (2012) developed six Neural Network (NN) models to predict the properties of concrete. Each model was trained and tested with their data set for training, testing and validation based on several values of Principal Component Variance (PCV), using the Bayesian regularization algorithm. The reason to train more models is to get the best Neural Network (NN) architecture, and the optimum PCV value. According to Boukhatem *et al.* (2012), the best architecture means that the optimal number of hidden neurons must have a NN in the hidden layer and hence increases the NN generalization capacity. The optimum value of PCV determined the Principal Component (PC) optimal number retained for each set of data and facilitates the NN training. After post-processing, a set of reduced and uncorrelated test data were produced and then integrated into the NN to get the output values for each test and validation set. This was based on calculating the sum of square errors which had a decreasing trend with the number of training cycles (iterations).

Bilgehan and Turgut (2010) tested a total of 238 concrete core samples using ultrasound for the determination of the velocities of the longitudinal ultrasonic waves before the execution of destructive compressive test of concrete. The cores were obtained from columns, shear or retaining walls in the reinforced concrete structures. The size of cores was 100 × 200 mm and no reinforcement existed in the cores, which are drilled horizontally through the thickness of the concrete elements. BS 1881 - 177 (1983) and

ASTM C42-90 (1992) procedures were used for determining the compressive strength of the cores. The velocity of the propagation of ultrasound pulses were measured by direct transmission using a Controls E-48 ultrasound device, which measured the time of propagation of ultrasound pulses with a precision of 0.10 μs. The transducers used were 50 mm in diameter, and had maximum resonant frequencies, as measured in laboratory conditions, of 54 kHz. The compressive strengths of the concrete cores are then converted to those of a cubical sample with 15 mm side length, according to BS 1881 (1983). The problem was then defined as a nonlinear input-output relation among the influencing factors, which are UPV, density of concrete specimens and compressive strength of concrete values, for ANN analyses. The typical multi-layer feed-forward ANNs consisted of an input layer, one or more hidden layer(s) and an output layer. All data were divided into two sets; one for the network learning (training) set and the other for testing set. Each of training and testing set covered approximately 50% of the total data. The data set was normalised before the analyses and the predictive capabilities of the feedforward back-propagation ANN are examined.

The methodology used for adjusting the weights was the momentum back-propagation with a delta rule, as presented by Rumelhart *et al.* (1986). Throughout all ANN simulations, the learning rates were used for increasing the convergence velocity. The sigmoid and linear functions were used for the activation functions of the hidden and output nodes, respectively. The hidden layer node numbers of each model were determined after trying various network structures, since no theory yet exists to clarify the number of hidden units needed to approximate a given function. The training phase was stopped after 5000 epochs; when the variation of error became sufficiently small. The computer program code for the ANN simulation, including neural networks toolbox, was written in MATLAB software. Various ANN architectures were tried and then the appropriate model structure was determined for the data sets. Numerous trials were carried out in the neural network environment to determine the neuron number of the hidden layers. Optimum hidden neuron numbers were obtained for different cases. The ANN model was then tested and the results were compared by means of root mean squared error, RMSE, and coefficient of determination, R^2, statistics. Gradient descent algorithm back-propagation learning rule was employed using tangent sigmoid (tansig) and logarithmic sigmoid (logsig) activation functions. Learning rate was 0.4 with training performance goal 10^{-5}, momentum constant 0.9 and maximum number of epochs 5000. After carrying out numerous trainings in the neural network simulation, the optimum hidden neuron number and hidden layer number were determined as 50 and 1, respectively.

Ikechukwu and Chidozie (2015) modelled the compressive strength of concretes incorporating termite mound soil using multi-layer perceptron networks. They used termite mound soil as part of concrete mixture. Their work showed the development of a computational model, based on artificial neural networks for the determination of compressive strength of concrete materials made by replacing the fine aggregate with termite mound soil. The work involved building a multi-layer perception neural network model which used experimental data obtained from compressive strength test of concrete made from termite mound soil. The compressive strength predicted were compared with predictions from an alternative model based on regression analysis. The results of the study showed that for the termite mound soil-based concrete, the regression model prediction has a correlation coefficient of 0.94402 and a sum of squares error of 0.72867100, while the neural network model prediction had a correlation coefficient of 0.94918 and a sum of squares error of 0.07629460. Generally, the models predicted well, but the neural network model predicted better than the regression model. The result of the study demonstrated a cheap, simple, very quick and accurate alternative to experimental method of concrete strength determination.

Pandelea *et al.* (2015) proposed a manner to verify the concrete samples homogeneity using artificial neural networks. The method proposed determined the percentages of various areas of component materials visible at top and bottom of a concrete cylinder having 20 cm diameter and 20 cm height. The training of the neural network was realised by using backpropagation algorithm and then, in order to separate the regions of interest Levenberg – Marquardt algorithm was used. After the network training with a number of neurons that varied between 10 to 30 and 10 to 1,000 iterations obtained various percentages of component materials. For the upper side of the cylinder, neural network with 30 neurons and 1000 iterations generated a percentage of 40.8866% rubber, 4.7264% aggregate and 52.6515% matrix. To the underside of the cylinder network with the same number of neurons and iterations like upper side generated the results: 28.5572% rubber, 4.1619% aggregate and 67.2809% matrix. The percentage was varied between both sides, 12.3294% for rubber, 0.5645% for aggregate and 14.6294% for matrix.

Gupta (2013) developed an ANN model for 28-day compressive strength. The model was trained with input and output experimental data. Correlation coefficient, RMSE and MAE are statistical values that are calculated for comparing experimental data with ANN model. As a result, the compressive strength values of concrete were predicted in the ANN models without attempting any experiments in quite a short period of time with some error rates, which could be minimized further by using other data mining techniques, such as, C5 method and fuzzy logic techniques. He also presented the actual and predicted values of 28 days compressive strength by using ANN technique. The correlation coefficient was found to be 0.8685.

It is for these accurate predictions that the ANN is employed in this work so as to predict the properties of concrete made with Bida natural gravel as coarse aggregate. However, it is necessary to base these predictions with experimental evaluation, hence the need for experimental designs.

2.7 Design of Experiment

Many experimental design textbooks and software packages emphasize the use of factorial and fractional factorial designs, where all factors in the experiment have two levels, often called 2k-p designs, where *k* is the number of factors, *p* is the degree of fractionation, and 2k-p is the number of runs. There are many good reasons for using only two levels per factor, including: reducing the size of the experiment, allowing for sequential experimentation, taking advantage of the relatively simple confounding properties of two-level fractional factorials, and allowing for simple graphical analysis of main effects and interactions (Box *et al.,* 1978).

Bisgaard (1997) discusses the advantages of two-level fractional factorials for technological experiments where all the factors are quantitative, meaning that the levels are measured or metered amounts that are usually continuous, but at least ranked. It is true that technological experiments often have only quantitative factors, however, it is not uncommon for technological experiments to also include factors that are qualitative in nature, such as, raw material type, supplier name, or die configuration. There are often more than two levels of such factors and since the levels cannot be ordered in any meaningful way, leaving out levels of such factors provides no information about the response's behavior at the omitted levels. In order to include multi-level qualitative factors, but maintain some of the useful characteristics of two-level fractional factorial experiments, a common practice is to use a simple coding scheme. Many authors have described this procedure including Taguchi (1987) and Montgomery (1997).

2.7.1 Factorial designs overview

Factorial designs allow for the simultaneous study of the effects that several factors may have on a process. When performing an experiment, varying the levels of the factors simultaneously rather than one at a time is efficient in terms of time and cost, and also allows for the study of interactions between the factors. Interactions are the driving force in many processes. Without the use of factorial experiments, important interactions may remain undetected (Box *et al.,* 1987; Montgomery, 1997; Pan 1996; Doug, 2015).

(a). Full factorial designs

In a full factorial experiment, responses are measured at all combinations of the experimental factor levels. The combinations of factor levels represent the conditions at which responses will be measured. Each experimental condition is called a "run" and the response measurement an observation. The entire set of runs is the design.

(b). Two-level full factorial designs

In a two-level full factorial design, each experimental factor has only two levels. The experimental runs include all combinations of these factor levels. Although two-level factorial designs are unable to explore fully a wide region in the factor space, they provide useful information for relatively few runs per factor. Because two-level factorials can indicate major trends, which can be used to provide direction for further experimentation.

(c). General full factorial designs

In a general full factorial design, the experimental factors can have any number levels. For example, Factor A may have two levels, Factor B may have three levels, and Factor C may have five levels. The experimental runs include all combinations of these factor levels. General full factorial designs may be used with small screening experiments, or in optimization experiments.

(d). Fractional factorial designs

In a full factorial experiment, responses are measured at all combinations of the factor levels, which may result in a prohibitive number of runs. To minimize time and cost, designs that exclude some of the factor level combinations can be used. Factorial designs in which one or more level combinations are excluded are called fractional factorial designs. Minitab generates two-level fractional factorial designs for up to 15 factors. Fractional factorial designs are useful in factor screening, because they reduce downwards the number of runs to a manageable size. The runs that are performed are a selected subset or fraction of the full factorial design. Minitab displays an alias table which specifies the confounding patterns. Because some effects are confounded and cannot be separated from other effects, the fraction must be carefully chosen to achieve meaningful results. Choosing the "best fraction" often requires specialized knowledge of the product or process under investigation undetected (Box *et al,* 1987; Montgomery, 1997; Pan, 1996; Doug, 2015).

(e). Plackett-Burman designs

Plackett-Burman designs are a class of resolution III, two-level fractional factorial designs that are often used to study main effects. In a resolution III design, main effects are aliased with two-way interactions. Minitab generates designs for up to 47 factors. Each design is based on the number of runs, from 12 to 48, and is always a multiple of 4. The number of factors must be less than the number of runs.

(f). Response Surface Designs

Response surface methods are used to examine the relationship between one or more response variables and a set of quantitative experimental variables or factors. These methods are often employed after identifying a “vital few” controllable factor and it is desired to find the factor settings that optimize the response (Box and Behnken, 1960; Box and Draper, 1987; Khuri and Cornell, 1987; Montgomery, 1997). Designs of this type are usually chosen when it is suspected that curvature in the response surface may occur. Response surface methods may be employed to;

i. find factor settings (operating conditions) that produce the "best" response

ii. find factor settings that satisfy operating or process specifications

iii. identify new operating conditions that produce demonstrated improvement in product quality over the quality achieved by current conditions

iv. model a relationship between the quantitative factors and the response

2.7.2 Mixture designs

Mixture experiments are a special class of response surface experiments in which the product under investigation is made up of several components or ingredients. Designs for these experiments are useful because many products design and development activities in industrial situations involve formulations or mixtures. In these situations, the response is a function of the proportions of the different ingredients in the mixture. For example, you may be developing a pancake mix that is made of flour, baking powder, milk, eggs, and oil. Or, you may be developing an insecticide that blends four chemical ingredients (Cornell, 1990; Montgomery and Voth, 1994; Meyers and Montgomery, 1995). In the simplest mixture experiment, the response (the quality or performance of the product based on some criterion) depends on the relative proportions of the components (ingredients). The quantities of components, measured in weights, volumes, or some other units, add up to a common total. In contrast, in a factorial design, the response varies depending on the amount of each factor (input variable). Minitab can create designs and analyse data from three types of experiments:

a. Mixture experiments

b. Mixture-amounts (MA) experiments

c. Mixture-process variable (MPV) experiments

2.7.4 Taguchi design overview

Taguchi is regarded as the foremost proponent of robust parameter design, which is an engineering method for product or process design that focuses on minimizing variation and/or sensitivity to noise. When used properly, Taguchi designs provide a powerful and efficient method for designing products that operate consistently and optimally over a variety of conditions. In robust parameter design, the primary goal is to find factor settings that minimize response variation, while adjusting (or keeping) the process on target. After you determine which factors affect variation, you can try to find settings for controllable factors that will either reduce the variation, make the product insensitive to changes in uncontrollable (noise) factors, or both. A process designed with this goal will produce more consistent output. A product designed with this goal will deliver more consistent performance regardless of the environment in which it is used (Peace, 1993).

Engineering knowledge should guide the selection of factors and responses. A robust parameter design is particularly suited for energy transfer processes; for example, a car's steering wheel is designed to transfer energy from the steering wheel to the wheels of the car. You should also scale control factors and responses so that interactions are unlikely. When interactions among control factors are likely or not well understood, you should choose a design that is capable of estimating those interactions. Minitab can help one to select a Taguchi design that does not confound interactions of interest with each other or with main effects. Noise factors for the outer array should also be carefully selected and may require preliminary experimentation. The noise levels selected should reflect the range of conditions under which the response variable should remain robust.

Robust parameter designs use Taguchi designs (orthogonal arrays), which allow one to analyze many factors with few runs. Taguchi designs are balanced, that is, no factor is weighted more or less in an experiment, thus allowing factors to be analysed independently of each other.

Minitab provides both static and dynamic response experiments.

a. In a static response experiment, the quality characteristic of interest has a fixed level.

b. In a dynamic response experiment, the quality characteristic operates over a range of values and the goal is to improve the relationship between an input signal and an output response.

The methodology employed in this research is described in chapter three in order to portray the importance of the reviewed methods and the absolute potency of the adopted one for this study.

CHAPTER THREE

3.0 MATERIALS AND METHODS

3.1 Materials

The materials used in this research are; water, ordinary Portland cement, fine river sand and Coarse aggregate (Bida Natural Gravel). The materials were tested in accordance with relevant standards and specifications to ascertain their suitability for making concrete.

3.1.1 Water

Water is necessary for mixing concrete to achieve the desired workability as well as for cement hydration. As such, potable drinking water from the tap in Civil Engineering Laboratory, Federal University of Technology, Minna was used for concrete mixing and curing in accordance to BS EN 1008 (2002).

3.1.2 Ordinary Portland cement (OPC)

Commercially available OPC categorised as CEM 1 (NIS 87:2004) was used to produce all concrete specimens in this research. The cement was sourced from local retailers within Minna metropolis and tested in accordance with BS EN 197- 1 (2000).

3.1.3 Fine river sand

Fine river sand was collected within Minna metropolis and prepared for concrete production.

3.1.4 Bida Natural Gravel (BNG)

BNG is a brownish-red naturally occurring stone in Bida, Niger State, Nigeria. It is found as a deposit in several metric tons in the middle of Niger Basin of Nigeria (Salihu, 2011; Nuhu, 2009). BNG was collected, washed and sun dried.

3.2 Methods

3.2.1 Moisture content test

Moisture content is the total amount of water contained in a material expressed as a percentage of the dry weight of the material. Moisture content is determined by measuring the loss of water in oven dried samples of aggregates. The test was conducted on fine aggregate (river sand) and BNG, and also in accordance to BS EN 12620 (2008), while using Equation (3.1) to calculate the moisture content.

$$\text{Moisture content} = \frac{W2 - W3}{W3 - W1} \times 100 \qquad (3.1)$$

Weight of empty moisture can $= W_1$

Weight of moisture can + sample (wet) $= W_2$

Weight of moisture can + sample (oven – dried) $= W_3$

3.2.2 Specific gravity (SG)

Specific gravity is the ratio of the mass of the aggregates sample to the mass of the same (absolute) volume of water. SG test was conducted on the fine aggregate and BNG. The relationship used to calculate SG is given in Equation 3.2. This test was conducted in accordance to BS EN 12620 (2008).

$$\text{Specific gravity} = \frac{W_2 - W_1}{W} \qquad (3.2)$$

$W = (W_4 - W_1) - (W_3 - W_2)$ weight of water displaced by sample

Weight of density bottle $= W_1$

Weight of density bottle + sample = W_2

Weight of density bottle + sample + water = W_3

Weight of density bottle + water = W_4

3.2.3 Bulk density

Bulk density test is an important characteristic that governs the amount of fine aggregates and cement paste that will fill the voids between coarse aggregates grains. Bulk density test was conducted on both fine and coarse aggregate. This test is a representation of the actual mass that fills a container of unit volume. Loose and compacted bulk density tests were conducted on the fine aggregates and BNG in accordance to BS EN 12620 (2008).

Weight of sample divider = W_1

Weight of sample divider + sample = W_2

Weight of sample = $W_2 - W_1 = W$

$$\text{Bulk density } = \frac{W}{V} \tag{3.3}$$

a. Loose or Compacted Bulk Density

The sample divider was weighed empty and recorded as W_1. The sample divider was filled using a scoop, the surface was then levelled with a straight edge, the sample divider and aggregate was weighed and the bulk density calculated as given in Equation 3.3.

The volume (V) of the sample divider = L x B x H (3.4)

Where:-

L = Length of sample divider

B= Breadth of sample divider

H = Height of sample divider

3.2.4 Aggregate Crushing Value Test (ACV)

ACV is a measure of the resistance of an aggregate to crushing under gradually applied load. It is expressed as a percentage to the first decimal place of the mass of fines formed to the total mass of the test specimen. The test was conducted on the BNG in accordance to BS 812 -110 (1990). ACV was calculated using Equation 3.5.

$$ACV = \frac{M_2}{M_1} 100\% \tag{3.5}$$

Where

M_1 = mass of the test specimen (in g);

M_2 = mass of the material passing the 2.36 mm test sieve (in g).

3.2.5 Aggregate impact value (AIV) test

AIV is a measure of the resistance of an aggregate to sudden shock or impact. The procedure outlined in BS 812 - 112 (1990) was followed. The test was conducted on BNG passing 14.0 mm test sieve and retained on a 10.0 mm test sieve. Aggregate sizes larger than 14 mm are not appropriate to the aggregate impact value test. Thus, AIV was calculated using Equation 3.6.

$$AIV = \frac{M_2}{M_1} 100\% \tag{3.6}$$

Where

M_1 = mass of the test specimen (in g);

M_2 = mass of the material passing the 2.36 mm test sieve (in g).

3.2.6 Sieve analysis

Sieve analysis was done to determine the grading of the aggregate samples. Aggregate sizes influence the strength of concrete and a well-graded aggregate sample is desired for concrete production. The procedure specified in BS EN 12620 (2008) for conducting sieve analysis for fine and coarse aggregates was followed.

3.2.7 Mix design

Mix design is aimed at establishing the most suitable and economic blend of constituent of concrete necessary for a trial batch to produce concrete similar to that which can achieve a good stability between the intended properties. The concrete components used for mix design include; water, cement, fine river sand and Bida natural gravel. The method of experiment was chosen bearing in mind the interrelationship and interaction between the concrete components, such that no mixture containing interaction between the constituents is discarded. As such, the multilevel factorial experimental design was used for this purpose. The absolute volume method thereafter, was used to obtain the quantity of each ingredient required in a cubic metre of concrete and consequently for the required volume.

3.2.7.1 Choice of parameters

The parameters selected for the study were chosen based on similar parameters used in previous successful studies as well as parameters suggested in standards (Shamsad, 2007; ACI 211, 2001; Shakhmenko and Birsh, 1998; Abbasi *et al.*, 1987; Soudki *et al.,* 2001). The parameters were selected bearing in mind the following:

(a) Water - cement ratio (w/c)

Three water-cement ratios were considered; 0.40, 0.50, 0.60. These w/c were chosen because they cover practically, a range of w/c ratio necessary for achieving concrete of adequate strength useful for a wide range of applications as obtained in literature. These w/c ratios have also been used in designing experiments in several studies (Shamsad, 2007; Shakhmenko and Birsh, 1998; Abbasi *et al.*, 1987; Soudki *et al.,* 2001). The w/c ratios lower than 0.4 were not considered because they are applicable for the production of high strength concrete. Also, any w/c ratio higher than 0.60 were not considered, because it is believed that the strength of concrete from such ratios will only be applicable for mass concreting.

(b) Coarse aggregate - total aggregate content ratio (ca/ta)

In other to achieve a concrete mix to meet workability and durability targets at minimum cost, ca/ta ratio is one of the important factors governing the arrival at such optimum concrete mix designs. For the purpose of this research, three ca/ta ratios were chosen, namely, 0.55, 0.60 and 0.65. These ratios were selected based on similar ratios used in previous studies and have been found to represent concrete within the practical strength range for normal strength concrete (Abbasi *et al.*, 1987; Alhaji, 2016).

(c) Total aggregate - cement (ta/c) ratio

Previous reviewed works using Bida Natural Gravel (BNG) as coarse aggregate used ta/c ratio in the range of 3 - 6 (Salihu, 2011; Alhaji 2016), while other works using crushed granite as coarse aggregate also suggested ta/c ratio within this region (Orr, 1972; Abbasi, *et al.*, 1987; Soudki, *et al.,* 2001). Therefore, in this research, a ta/c ratio of 3.00, 4.50 and 6.00 was used. This was chosen because blending lower levels of w/c ratio with higher levels of ta/c ratio will result in dry mixes. Similarly, blending higher w/c ratios with lower levels of ta/c is likely to result in very wet mixes. Based on the parameters chosen, random runs were selected to carry out trial mixes. Consistent mixes were obtained for the chosen runs from the sample space of the experiment.

3.2.7.2 Multilevel full factorial design

Multilevel full factorial design was used so as to accommodate various combinations of factors and their respective levels. Based on the factors and their levels, MINITAB (2017) produced 27 experimental runs as shown in Table 3.1. Nine separate mixes were prepared for the purpose of validating the model produced.

Table 3.1: Experimental runs selected by Minitab

Run Order	Coded Factors			Uncoded Factors		
	A	B	C	A	B	C
1	3	2	2	0.6	0.60	4.50
2	2	1	3	0.5	0.55	6.00
3	1	1	1	0.4	0.55	3.00
4	3	1	3	0.6	0.55	6.00
5	2	3	1	0.5	0.65	3.00
6	2	1	1	0.5	0.55	3.00
7	1	3	2	0.4	0.65	4.50
8	3	3	2	0.6	0.65	4.50
9	3	3	1	0.6	0.65	3.00
10	3	1	2	0.6	0.55	4.50
11	1	1	2	0.4	0.55	4.50
12	2	2	1	0.5	0.60	3.00
13	2	2	2	0.5	0.60	4.50
14	3	1	1	0.6	0.55	3.00
15	2	3	3	0.5	0.65	6.00
16	1	3	1	0.4	0.65	3.00
17	1	2	1	0.4	0.60	3.00
18	2	1	2	0.5	0.55	4.50
19	1	1	3	0.4	0.55	6.00
20	3	3	3	0.6	0.65	6.00
21	1	3	3	0.4	0.65	6.00
22	2	2	3	0.5	0.60	6.00
23	3	2	3	0.6	0.60	6.00
24	1	2	2	0.4	0.60	4.50
25	1	2	3	0.4	0.60	6.00
26	3	2	1	0.6	0.60	3.00
27	2	3	2	0.5	0.65	4.50

3.2.7.3 Absolute volume equation

For the purpose of obtaining the required quantity of ingredients in a cubic metre of concrete as well as the quantities required for preparing samples for different tests, the absolute volume method was used. The quantity required for one cubic meter of concrete is presented in Table 3.2, while the required quantity for each specimen is shown in Table 3.3. The equation essential for the calculation of weight of cement required in a cubic metre of concrete was derived from the absolute volume equation, thus;

Absolute volume is given by;

$$Vw + Vc + Vfa + Vca + Vv = 1 \tag{3.7}$$

$$\frac{Ww}{1000Gw} + \frac{Wc}{1000Gc} + \frac{Wfa}{1000Gfa} + \frac{Wca}{1000Gca} + Vv = 1\text{; using 2\% air void,} \tag{3.8}$$

$$\frac{Ww}{1000Gw} + \frac{Wc}{1000Gc} + \frac{Wfa}{1000Gfa} + \frac{Wca}{1000Gca} + 0.02 = 1 \tag{3.9}$$

where,

Vw = volume of water

Vc = volume of cement

Vfa = volume of fine aggregate

Vca = volume of coarse aggregate

Vv = volume of air void

Ww = weight of water

Wc = weight of cement

Wfa = weight fine aggregate

Wca = weight coarse aggregate

Gw = specific gravityof water

Gc = specific gravity of cement

Gfa = specific gravity of fine aggregate

Gca = specific gravity of coarse aggregate

Given that;

$$Ww = \left(\frac{Ww}{Wc}\right)Wc \tag{3.10}$$

$$W_{FA} = \left(1 - \frac{W_{CA}}{W_{TA}}\right)\left(\frac{W_{TA}}{W_C}\right)W_C \tag{3.11}$$

$$W_{CA} = \left(\frac{W_{TA}}{Wc}\right)\left(\frac{W_{CA}}{W_{TA}}\right)Wc \tag{3.12}$$

Substituting the values of $W_W, W_{FA}, and W_{CA}$ into the absolute volume equation and making Wc the subject of the formula gives Equation 3.13 that was used to estimate the volume of cement required in a cubic meter of concrete.

Deleted[ENGR. A. YUSUF]: an equation

Deleted[ENGR. A. YUSUF]: can be

$$W_C = \frac{1 - V_V}{\dfrac{\left(\dfrac{W_W}{W_C}\right)W_C}{1000G_W} + \dfrac{1}{1000G_C} + \dfrac{\left(1 - \dfrac{W_{CA}}{W_{TA}}\right)\left(\dfrac{W_{TA}}{W_C}\right)W_C}{1000G_{FA}} + \dfrac{\left(\dfrac{W_{TA}}{W_C}\right)\left(\dfrac{W_{CA}}{W_{TA}}\right)W_C}{1000G_{CA}}} \tag{3.13}$$

Table 3.2: Quantities required for batching

Run Order	w/c	Water (kg/m^3)	Cement (kg/m^3)	Fine Aggregate (kg/m^3)	Coarse Aggregate (kg/m^3)
1	0.6	221.56	369.27	664.69	997.03
2	0.5	156.26	312.52	843.80	1031.31
3	0.4	208.88	522.21	704.98	861.64
4	0.6	181.72	302.86	817.72	999.44
5	0.5	248.29	496.58	521.41	968.33
6	0.5	247.90	495.79	669.32	818.05
7	0.4	159.90	399.75	629.61	1169.27
8	0.6	221.76	369.60	582.12	1081.08
9	0.6	283.58	472.63	496.26	921.63
10	0.6	221.37	368.94	747.11	913.13
11	0.4	159.59	398.98	807.94	987.49
12	0.5	248.09	496.18	595.42	893.13
13	0.5	191.87	383.73	690.71	1036.07
14	0.6	283.15	471.92	637.09	778.66
15	0.5	156.57	313.15	657.60	1221.27
16	0.4	209.23	523.09	549.24	1020.02
17	0.4	209.06	522.65	627.18	940.76
18	0.5	191.69	383.38	776.34	948.86
19	0.4	129.12	322.81	871.59	1065.28
20	0.6	182.07	303.45	637.24	1183.45
21	0.4	129.39	323.48	679.31	1261.58
22	0.5	156.42	312.83	750.79	1126.19
23	0.6	181.89	303.15	727.57	1091.35
24	0.4	159.75	399.37	718.86	1078.29
25	0.4	129.26	323.15	775.55	1163.33
26	0.6	283.36	472.27	566.73	850.09
27	0.5	192.04	384.08	604.93	1123.45

Table 3.3: Quantities of materials required at each sample point

Run	w/c	ca/ta	ta/c	Volume required (m^3)	Water (kg/m^3)	Cement (kg/m^3)	Fine Aggregate (kg/m^3)	Coarse Aggregate (kg/m^3)
1	0.6	0.6	4.5	0.04	9.19	15.31	27.56	41.34
2	0.5	0.55	6	0.04	6.48	12.96	34.98	42.76
3	0.4	0.55	3	0.04	8.66	21.65	29.23	35.72
4	0.6	0.55	6	0.04	7.53	12.56	33.90	41.44
5	0.5	0.65	3	0.04	10.29	20.59	21.62	40.15
6	0.5	0.55	3	0.04	10.28	20.56	27.75	33.92
7	0.4	0.65	4.5	0.04	6.63	16.57	26.10	48.48
8	0.6	0.65	4.5	0.04	9.19	15.32	24.14	44.82
9	0.6	0.65	3	0.04	11.76	19.60	20.58	38.21
10	0.6	0.55	4.5	0.04	9.18	15.30	30.98	37.86
11	0.4	0.55	4.5	0.04	6.62	16.54	33.50	40.94
12	0.5	0.6	3	0.04	10.29	20.57	24.69	37.03
13	0.5	0.6	4.5	0.04	7.95	15.91	28.64	42.96
14	0.6	0.55	3	0.04	11.74	19.57	26.41	32.28
15	0.5	0.65	6	0.04	6.49	12.98	27.27	50.64
16	0.4	0.65	3	0.04	8.68	21.69	22.77	42.29
17	0.4	0.6	3	0.04	8.67	21.67	26.00	39.01
18	0.5	0.55	4.5	0.04	7.95	15.90	32.19	39.34
19	0.4	0.55	6	0.04	5.35	13.38	36.14	44.17
20	0.6	0.65	6	0.04	7.55	12.58	26.42	49.07
21	0.4	0.65	6	0.04	5.36	13.41	28.17	52.31
22	0.5	0.6	6	0.04	6.49	12.97	31.13	46.69
23	0.6	0.6	6	0.04	7.54	12.57	30.17	45.25
24	0.4	0.6	4.5	0.04	6.62	16.56	29.80	44.71
25	0.4	0.6	6	0.04	5.36	13.40	32.16	48.23
26	0.6	0.6	3	0.04	11.75	19.58	23.50	35.25
27	0.5	0.65	4.5	0.04	7.96	15.92	25.08	46.58
V1	0.55	0.55	3.50	0.04	10.07	18.30	28.83	35.24
V2	0.55	0.45	5.50	0.04	7.45	13.55	40.99	33.54
V3	0.55	0.55	5.50	0.04	7.45	13.59	33.62	41.09
V4	0.44	0.55	3.50	0.04	8.41	19.29	30.39	37.14
V5	0.45	0.45	5.50	0.04	6.31	14.02	42.41	34.70
V6	0.45	0.55	5.50	0.04	6.32	14.05	34.77	42.49
V7	0.40	0.65	5.00	0.04	6.15	15.37	26.89	49.94
V8	0.60	0.65	5.00	0.04	8.57	14.29	25.00	46.43
V9	0.50	0.65	5.00	0.04	7.40	14.81	25.91	48.12

3.2.8 Production of concrete using BNG

The production routine of concrete to satisfy pre-defined performance criteria has a direct relationship with the quality of the resulting concrete. Mix design, mixing of concrete constituents, curing and test methods have been identified as factors that govern the quality of the resulting concrete (Aītcin, 1998; Mehta and Monteiro, 2014; Neville and Aitcin, 1998; Olawuyi, 2016). The aggregates, water and cement were weighed and a mini concrete mixer was used for the mixing. The fine aggregate was first put in the mixer and the cement was added to it while the mixture was mixed for 60 seconds. BNG was then added to the mixture and mixing continued for another 60 seconds. Half of the required water was added to the mixture and the other half after mixing for 60 seconds. The mixing was extended for an additional 120 seconds as recommended in literature so as to achieve an adequate mixed concrete (Aītcin, 1998, Abdullahi, 2009; Mehta & Monteiro, 2014). Table 3.3 shows the number of test specimens that was produced for the experiments.

Table 3.3: Number of required specimens

S/N	Concrete Specimen	28-day testing
1	150x150x150 mm cube	81
2	100x100x500 mm prism	81
3	100x200 mm cylinder	81
4	100x200 mm cylinder	81

For each of the mix combination suggested by MINITAB, concrete was prepared and the slump loss was examined in accordance to BS EN 12350 - 6 (2009). Three concrete cubes were prepared for compressive strength test, 3 prisms for flexural strength test and 6 cylinders were produced for splitting tensile strength and modulus of elasticity tests. The hardened concrete was cured in the curing tank for 28 days after which the strength tests and modulus of elasticity were carried out.

3.2.9 Test on hardened concrete

150 x 150 x 150mm cubes, 100 x 100 x 500 mm beams and 100 x 200 mm cylinders were cast, covered with thick polythene and allowed to set for 24 hours. The samples were demoulded after 24 hours and cured for 28 days. The cured samples were thereafter tested for compressive strength according to BS EN 12390 - 3 (2009), flexural strength according to BS EN 12390 - 5 (2009), tensile splitting test in accordance to BS EN 12390 - 6 (2009), and modulus of elasticity in accordance to BS EN 12390 - 13 (2009).

3.2.10 Model development

The model was developed using MATLAB (2015) from MathWorks. Before developing the Artificial Neural Network (ANN), various ANN architectures were tried to select the best architecture. The network was trained to recognise, process and interpret inputs and translate to outputs based on data fed into the system. This procedure is explained below in (a) to (e).

a. Design of the ANN architecture

A multilayer feed-forward ANN architecture with a single hidden layer was adopted because it has been adjudged efficient in its generalisation ability (Kartam *et al.,* 1997; Flood and Kartam 1994a; Flood and Kartam 1994b). Development of the ANN architecture requires the selection of the number of inputs, and outputs. The number of neurons in each layer (input, hidden and output), the type of activation function, the assignment of weights and biases as well as the selection of the training algorithm. Water/cement ratio (w/c), weight of water (Ww), weight of cement (Wc), weight of fine aggregate (Wfa) and weight of BNG (W_{BNG}) was used as inputs while slump, compressive strength, flexural strength, split tensile strength and modulus of elasticity served as the output in each of the ANN models developed. Between the input and output layer, 1 hidden layer was selected with 2 neurons up to a maximum of 50 neurons. The network was allowed to randomly assign weights and biases to the network and logsig and tansig activation functions were tried for the hidden layers while the linear activation function (pureline) was selected for the output layer in each of the models developed. The characteristics of the activation function used are as given in Table 3.4 and the model equation for the two cases (logsig and tansig) considered are as given in Equations 3.9 to 3.11.

Table 3.4: Activation functions adopted in the study

Activation Function	Equation	Derivative	Range
Purlin (Linear)	$f(x) = x$	$f'(x) = 1$	-∞ to ∞
Log Sigmoid	$f(x)\dfrac{1}{1+e^{-x}}$	$f'(x) = f(x)(1 - f(x))$	0 to 1
Tan Sigmoid	$f(x) = \dfrac{2}{1+e^{-2x}} - 1$	$f'(x) = (1 - f(x)^2)$	-1 to 1

b. Preparing training, validation and test data sets

ANN is structured to function like the human brain. As such, it performs knowledge acquisition from interconnection of inputs data (x) and corresponding output data (y) based on an iteration process of weight (coefficient) and in most cases bias (constant) adjustments up until the error between the actual output (experimental results) and model output is negligible in line with preselected performance metrics as shown in Figure 3.1. This process is known as the back-propagation training algorithm and was adopted in this study. New sets of input data are supplied to the network based on fixed weights and bias of final training process to generate outputs depending on the learnt input/output pair.

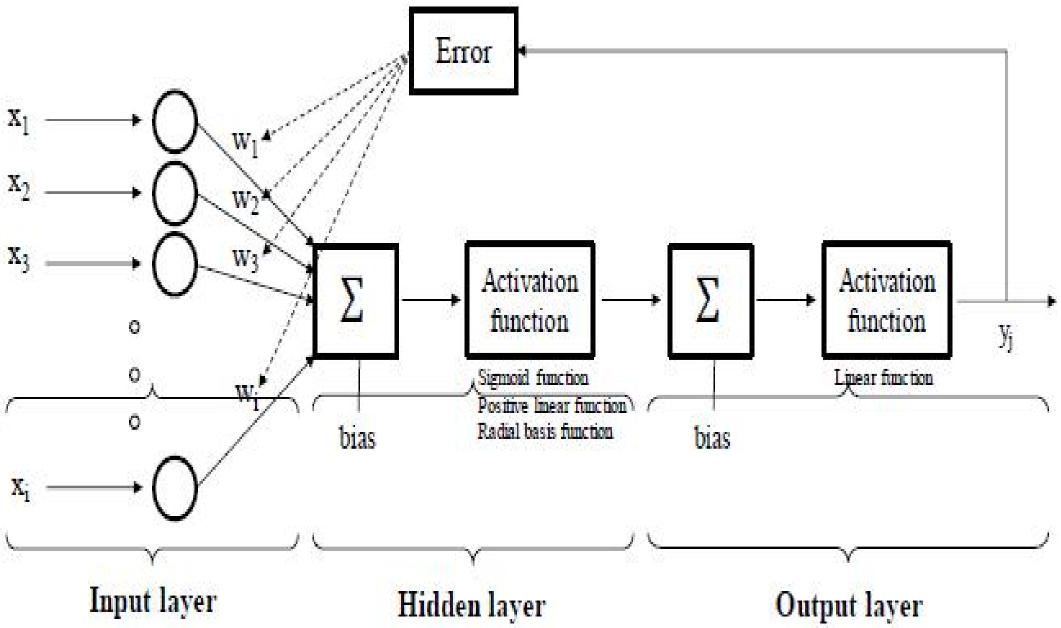


Figure 3.1: Mode of operation of the artificial neural network

The input and output data pairs were augmented using a MATLAB (2015) script shown in Figure 3.2 and the 180 augmented data sets are presented in Appendix A. 100 data points from the augmented data were used for training, 20 data points were used for validation and 60 data points were used for testing the ANN model.

```
%AUG augmented a 1-D data
%   This function creats an additional N-times data point by
%   randomly adding Guassian number between the minimum and maximum values
%   of the data.

a = A;
i = 1;
while i < N*length(A)

    for j = 1:length(A)
        sta = min(A);
        ma = max(A);
        a(i,:) = sta+(ma-sta)*rand;


        i = i+1;
    end
end

newA = [A;a];
end
```

Figure 3.2: MATLAB script used for data augmentation

c. Pre-processing input data sets

ANN input data sets are often not on the same numerical scale. Activation functions used to transform weighted sum of inputs to give outputs are usually nonlinear functions of sigmoid nature. These functions are typically sensitive to data within specific range. Furthermore, experimental data usually contain noisy and omitted observations and in most cases of inconsistent nature. Procedures encompassing data reduction, data transformation, data integration, data cleaning and data normalisation have been reported to improve the effectiveness and precision of ANN models. In order to fairly judge the neural network identities, data normalisation was performed on the input data sets. Consequently, min-max normalisation technique shown in Equation 3.14 was used to transform the input data to a uniform scale between -1 and +1. This method has been reported to be effective for sigmoid activation function, which is adopted in this study.

Deleted[ENGR. A. YUSUF]: 6

$$Nd = \left(\frac{x - xmin}{xmax - x\ min}\right) \tag{3.14}$$

Where;

Nd is the normalized data

x = input data

xmin = minimum value of the data x and

xmax = maximum value of the data x.

d. The artificial neural network model

Input data sets were supplied to the neurons in the input layer and were each treated with coefficients and constants known as weights and bias respectively to obtain a sum of weighted inputs and bias as given in Equation 3.15.

Deleted[ENGR. A. YUSUF]: 7

$$\rho = \sum_{i=1}^{n} xi.wij + b1 \tag{3.15}$$

Where;

ρ = weighted sum of input and bias

xi = input data i

wij = weight associated with the input-hidden layer and

b1 is the constant associated with input-hidden layer.

Equation 3.15 was treated with a tangent sigmoid activation function given in Equation 3.16 to obtain the first layer output given in Equation 3.17.

Deleted[ENGR. A. YUSUF]: 7

Deleted[ENGR. A. YUSUF]: 1

Deleted[ENGR. A. YUSUF]: 8

$$\beta = \frac{2}{1+e^{-2x}} - 1 \qquad (3.16)$$

Where;

β = activation function

$$\boldsymbol{\phi} = \beta \sum_{i=1}^{n} xi.wij + b1 \qquad (3.17)$$

Where;

$\boldsymbol{\phi}$ is the hidden layer output.

The first (hidden) layer output $\boldsymbol{\phi}$ was supplied to the neuron in the output layer and were further processed with new weights and bias. The weighted sum was further treated with a linear activation function given in Equation 3.18 to obtain the overall model output given in Equation 3.19 termed as the case 1 model.

Deleted[ENGR. A. YUSUF]: 20

Deleted[ENGR. A. YUSUF]: 21

$$f(x) = x \qquad (3.18)$$

$$\boldsymbol{\xi} = \mu(\sum_{i=1}^{n} wij \,.\, \boldsymbol{\phi} + b2) \qquad (3.19)$$

Where;

$\boldsymbol{\xi}$ = output of the entire case 1 ANN model

μ = linear activation function $f(x)$

wij = weight associated with the output layer and

b2 = bias associated with the output layer

Similarly, logsig activation function shown in Equation 3.20 was used to treat the weighted input sum ρ given in Equation 3.15 to obtain the first hidden layer output given in Equation 3.21.

Deleted[ENGR. A. YUSUF]: 2
Deleted[ENGR. A. YUSUF]: 7
Deleted[ENGR. A. YUSUF]: 3

$$\varphi = \frac{1}{1+e^{-x}} \quad (3.20)$$

$$\boldsymbol{\nabla}_{\text{hidden}} = \varphi \sum_{i=1}^{n} xi.wij + b1 \quad (3.21)$$

Where;

$\boldsymbol{\nabla}_{\text{hidden}}$ = output of the hidden layer and

$\boldsymbol{\varphi}$ = logsig activation function

The first (hidden) layer output $\boldsymbol{\nabla}_{\text{hidden}}$ was supplied to the neuron in the output layer and were further processed with new weights and bias. The weighted sum was treated with a linear activation function given in Equation 3.18 to obtain the overall model output given in Equation 3.22 termed as the case 2 model.

Deleted[ENGR. A. YUSUF]: 20
Deleted[ENGR. A. YUSUF]: 4

$$\boldsymbol{\psi}_{\text{output}} = \mu\left(\sum_{i=1}^{n} wij\,.\nabla + b2\right) \quad (3.22)$$

Where;
$\boldsymbol{\psi}_{\text{outpu}}$ = output of the entire case 2 ANN model

e. Evaluation of the ANN model

The models were trained using back propagation algorithm. The sequence requires updating the connection weights and biases according to the learning capacity of the network. The iterative process lasted up until the network was able to identify the smallest error between the actual experimental result and the model output based on the parameters given in Table 3.5. The performance of the trained model was examined using Mean Square Error (MSE), Root Mean Square Error (RMSE) and Regression (R) given in Equations 3.23, 3.24 and 3.25 respectively. The MSE is a measure of the average of the square of the difference between the experimental result and the model output. It also depicts the deviation of the predicted output from the actual output. Thus,

Deleted[ENGR. A. YUSUF]: 5
Deleted[ENGR. A. YUSUF]: 6
Deleted[ENGR. A. YUSUF]: 7

the smaller the MSE, the smaller the error margin and the better the model. RMSE denotes the standard deviation of the prediction errors or the residual. It is a measure of the concentration of the data points around the line of best fit. R value range from 0 to 1 or from 0 to 100 percent with values closer to 100% signifying a high goodness of fit.

Table 3.5: Parameters used to train the feed forward ANN models

Parameter	Configuration
Input data	w/c, water, cement, sand and BNG content
Output data	Slump, Compressive, flexural and splitting tensile strengths and modulus of elasticity
Maximum number of epochs	10
Performance goal	0.000001
Learning Rate	0.01
Momentum constant	0.9
Training function	TrainLM
Activation function	Hidden layer – Tansig and logsig; Output layer - Purelin
ANN architectures tried	2:50 in steps of 2

$$MSE = \frac{\sum_{i=1}^{n}(output(i) - actual(i))^2}{n} \quad (3.23)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(output(i) - actual(i))^2}{n}} \quad (3.24)$$

$$R = \left[\frac{\sum_{i=1}^{n}(actual(i) - \overline{actual(i)})(output(i) - \overline{output(i)})}{\sum_{i=1}^{n}(actual(i) - \overline{actual(i)})^2 \sum_{i=1}^{n}(output(i) - \overline{output(i)})^2}\right]^2 \quad (3.25)$$

Where;

Output (i) = output obtained from ANN model for each of the properties of concrete considered.

Actual (i) = actual experimental result for each of the properties of concrete considered.

$\overline{actual(i)}$ = average actual data,

$\overline{output(i)}$ = average output from the ANN model and

n is the sample size.

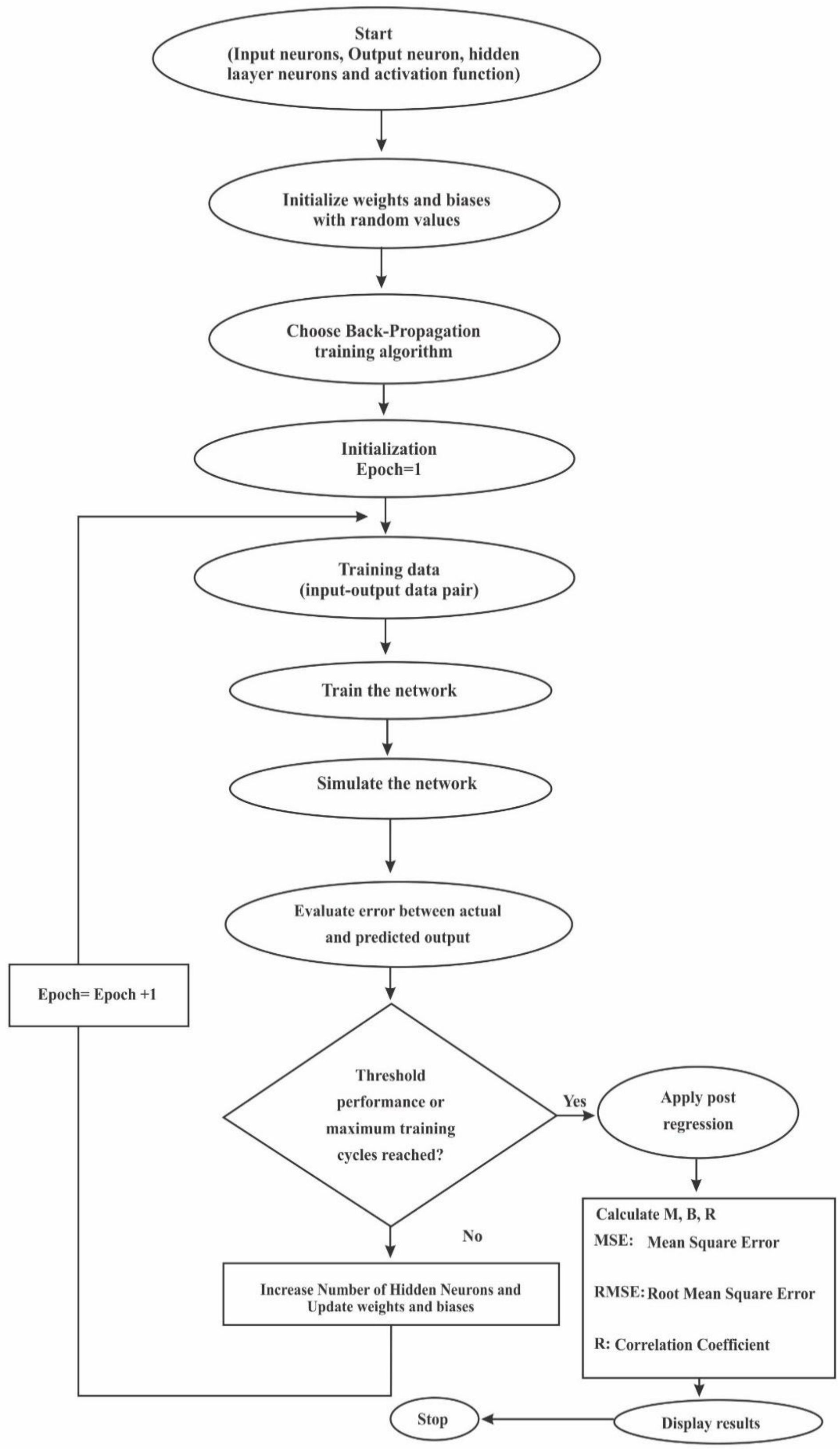


Figure 3.3: Flow chart showing the algorithm of the ANN model used.

CHAPTER FOUR

4.0 RESULTS AND DISCUSSION

4.1 Preliminary Test Results of Fine and Coarse Aggregates

4.1.1 Moisture content

The moisture inherent in an aggregate is the amount of water exceeding that at the saturated and surface dry condition. Moisture content contributes to the water demand of concrete and is of great importance when designing concrete mixtures. The moisture content of the coarse and fine aggregates used is as shown in Table 4.1. Acceptable moisture content of aggregate in concrete stipulated by Neville (2011) is in the region of 0 to 1 % for coarse aggregates and 1 to 10 % for fine aggregates. From Table 4.1, the moisture content of both aggregates is within limits. This indicate that mix adjustment is not necessary in order not to cause great variability in the concrete produced.

Table 4.1: Moisture content of aggregate

	Coarse Aggregate (BNG)		Fine Aggregate (Sand)	
Trial	Trial 1	Trial 2	Trial 1	Trial 2
Can no.	Y3	P2	F3	I9
weight of can (g)	25.3	24.5	27.8	26.7
weight of can + wet sample (g)	79.9	93.5	83.5	75.5
weight of can + dry sample(g)	79.6	93.2	82.1	74.6
weight of water (g)	0.3	0.3	1.4	0.9
weight of dry sample (g)	54.3	68.7	54.3	47.9
Moisture content (%)	0.55	0.44	2.58	1.88
Average Moisture Content (%)	0.50		2.23	

4.1.2 Specific gravity

Specific gravity was determined from a representative sample of the coarse and fine aggregates used. Table 4.2 shows the result of specific gravity for the coarse and fine aggregates obtained from three trials. The specific gravity of the natural coarse aggregate was 2.62 while that of the sand was 2.60. Neville (2011) recommended that specific gravity of coarse and fine aggregates should be between 2.5 - 3.0 and 2.6 - 2.7 respectively. The aggregates used were therefore within the specified range of specific gravity.

Table 4.2: Specific gravity of coarse and fine aggregate

	BNG			Fine Aggregate		
Trial	1	2	3	1	2	3
weight of cylinder (g)	555.5	585.8	580.1	69	116.5	394
weight of cylinder + Sample (g)	872.3	954.8	955.8	136.5	286.8	542.3
weight of cylinder + Sample + water (g)	1745.8	1812	1795.1	210.3	461.6	926.2
weight of cylinder + water (g)	1549.9	1585.1	1561.1	168.2	359.4	837.3
Specific Gravity	2.62	2.60	2.65	2.66	2.50	2.50
Average Specific Gravity		2.62			2.60	

4.1.3 Bulk density

BS 812 - 2 (1995) specifies two degrees of compaction of aggregates for concrete. The uncompacted (loose) and compacted bulk densities. The loose and compacted bulk densities of the aggregates used are presented in Table 4.3 and range between 1634.06 to 1939.28 kg/m^3. The bulk density of aggregates usually used in normal weight concrete is between 1200 and 1950 kg/m^3 (Jackson and Dhir, 1996; Abdullahi, 2006), it is therefore within this range. The aggregate is thus suitable for concrete production.

Table 4.3: Bulk density of coarse and fine aggregate

	Uncompated			Uncompacted		
Trail	1st	2nd	3rd	1st	2nd	3rd
		BNG			River sand	
volume of mould	0.00023	0.00023	0.00023	0.00023	0.00023	0.00023
weight of mould (g)	266.7	266.7	266.7	266.7	266.7	266.7
weight of mould + sample (g)	661.8	665.4	670.2	649.2	637.6	640.8
Weight of sample (g)	395.1	398.7	403.5	382.5	370.9	374.1
Bulk Density (kg/m^3)	1717.83	1733.48	1754.35	1663.04	1612.61	1626.52
Average Bulk Density (kg/m^3)		1735.22			1634.06	
		Compacted			Compacted	
weight of mould (g)	266.7	266.7	266.7	266.7	266.7	266.7
weight of mould + sample (g)	706.8	720	711.4	663.3	662.9	666.7
Weight of sample (g)	440.1	453.3	444.7	396.6	396.2	400
Bulk Density (kg/m^3)	1913.48	1970.87	1933.48	1724.35	1722.61	1739.13
Average Bulk Density (kg/m^3)		1939.28			1728.70	
Void Ratio		0.89			0.95	

4.1.3 Water absorption

The water absorption of aggregate are measured within 24 hours based on BS 812 - 2 (1995) guidelines. BS 882 (1992), specifies that aggregates for concrete should possess water absorption of not more than 3 %. Gupta (2013), however, opined that water absorption of coarse aggregates should lie between 0.5 to 1%, while that of fine aggregates should be in the range 0.1 to 5%. The water absorption of the aggregates used are as depicted in Table 4.4. It is evident that the aggregates have WA well within the range specified by BS 812 – 2 (1995) but does not conform to the recommendations of Gupta (2013). However, it is safe to use these aggregates for concrete production.

Table 4.4: Water absorption of coarse and fine aggregate

Deleted[ENGR. A. YUSUF]:

	BNG			River Sand		
	1st trial	2nd trial	3rd trial	1st trial	2nd trial	3rd trial
Weight of can (g)	s40.5	39.3	51	52.9	60.9	53.6
Weight of can + dry soil (g)	189.3	222.5	191.1	213.2	263	288.9
Weight of can + wet soil (g)	192.5	225.4	194	252.5	311.7	308.1
Weight of dry soil (g)	148.8	183.2	140.1	160.3	202.1	235.3
Weight of wet soil (g)	152	186.1	143	199.6	250.8	254.5
Water Absorbtion (%)	2.15	1.58	2.07	2.45	2.41	0.82
Avearage Water Absorption (%)		1.93			1.89	

4.1.4 Aggregate crushing value

The coarse aggregate crushing value was determined and the result is as shown in Table 4.5. The aggregate crushing value is an index which defines the strength of an aggregate and is applicable in pavement and road construction. BS 812 - 110 (1990) specifies ACV values less than 30% is desirable in concretes used in roads and pavements. The ACV obtained for the BNG was 27.27 % as shown in Table 4.5. This depicts that the aggregates possess considerable strength and can be used as a pavement material.

Table 4.5: Crushing value of coarse aggregate (BNG)

	Trial		
	A	B	C
Weight of mould (g)	4500	4500	4500
Weight of sample+ mould (g)	8049.5	8032.8	8025.5
Weight of Compacted sample (M_1) (g)	3549.5	3532.8	3525.5
Wt. of sample passing 2.35 sieve (M_2) (g)	950.5	967.2	974.5
Aggregate Crushing Value (ACV) = (M_2/M_1) x 100	26.78	27.38	27.64
Average ACV (%)	27.27		

4.1.5 Aggregate impact value (AIV)

The coarse aggregate impact value was determined and the result is as given in Table 4.6. BS 812 - 112 (1990) specifies that coarse aggregates with AIV greater than 30% should be treated with caution due to their low impact value. This implies that AIV values should be less than 30%. Furthermore, aggregates with AIV value between 19 and 28 % should be regarded as a mixed gravel. The coarse aggregate is therefore a mixed gravel with AIV of 24.10 % sufficient to withstand sudden shock or impact. The aggregate used (BNG) possesses the required AIV value and is suitable for use in concrete production.

Table 4.6: Aggregate impact value of coarse aggregate

	Trial		
	A	B	C
Weight of mould (g)	2400	2400	2400
Weight of sample+ mould (g)	3400	3300	3355
Weight of sample (M_1) (g)	1000	900	955
Wt. of sample passing 2.35 sieve (M_2) (g)	250	200	240
Aggregate Impact Value (AIV) = (M2/M1) x 100	25	22.2	25.1
Average AIV (%)	24.10		

4.1.6 Sieve analysis

4.1.6.1 Sieve analysis for coarse aggregate (BNG)

Sieve analysis was conducted on the coarse aggregate to ascertain its suitability for concrete production. The sieve analysis result for coarse aggregate as well as the grading curve is as presented in Table 4.6 and Figure 4.1 respectively. BS 882 (1992) stipulates grading limits for coarse aggregates of size 20 mm – 5 mm to be used in concrete as given in Table 4.7. Sieve size 10 mm does not conform to this limit. This implies that the aggregate contains large proportion of particles between 14mm and 10mm. Studies have shown that the smaller the size of coarse aggregate, the higher the strength of the resulting concrete. It is therefore appropriate to use this aggregate for the production of concrete. Furthermore, the grading characteristics of aggregates are described by the coefficient of uniformity (Cu) and coefficient of curvature (Cc) values. Well-graded aggregates should possess Cc values between 1 and 3. Cu and Cc values are calculated as;

$$Cu = \frac{D_{60}}{D_{10}} = 1.63$$

$$Cc = \frac{{D_{30}}^{2}}{D_{60} x D_{10}} = 1.24$$

D_{10}, D_{30} and D_{60} values were traced from the grading curve as 9.5, 13.5 and 16.5 respectively. Since the Cc value is greater than 1, but less than 3, the aggregate is said to be well graded according to Craig (2004).

Table 4.7: Sieve analysis of coarse aggregate

Sieve Size (mm)	Mass Retained (g)	Percentage Mass Retained (%)	Cumulative Percentage Mass Retained (%)	Percentage Passing (%)	Grading Limits Prescribed by BS 882 (%)
20	100	2	2	98	90 - 100
14	2700	54	56	44	40 - 80
10	1600	32	88	12	30 - 60
6.3	400	8	96	4	
5	200	4	100	0	0 - 10
Total	**5000**				

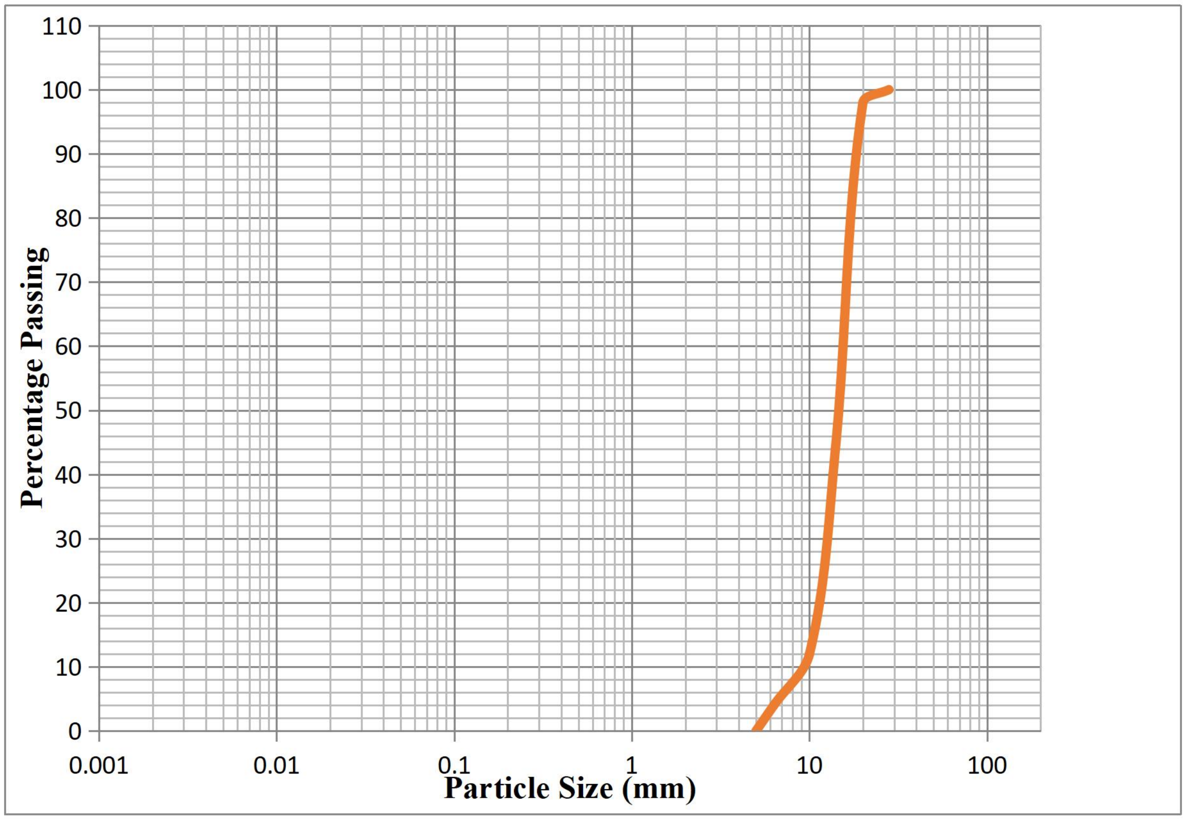


Figure 4.1: Particle size distribution curve for coarse aggregate

4.1.6.2 Sieve analysis for fine aggregate

The results of the sieve analysis of the fine aggregate (sand) used is as given in Table 4.8 while the grading curve is presented in Figure 4.2. The sand satisfied the grading limits specified by BS 882 (1992). Fineness modulus, Cu and Cc of the sand was determined in order to examine its suitability for concrete making. The fineness modulus obtained was 2.66 indicating that the majority of the aggregate lies between 0.30 and 0.60 mm. This indicate that the sand was coarse in nature. The Cu and Cc was 3 and 1.23 respectively. The sand can therefore be said to be well-graded and suitable for concrete production.

Table 4.8: Sieve analysis of fine aggregate

Sieve size (mm)	Weight of sieve (g)	weight of sieve + sample (g)	Percentage retained (%)	Cumulative percentage retained (%)	Percentage passing (%)	Grading Limits Prescribed by BS 882 (%)
5	475.1	477.1	0.4	0.4	99.6	98 - 100
3.35	467.8	476.9	1.82	2.22	97.78	
2.36	433.7	447.8	2.82	5.04	94.96	60 - 100
2	416.5	429.1	2.52	7.56	92.44	
1.18	384.9	456.3	14.28	21.84	78.14	30 - 100
850	352	415.2	12.64	34.48	65.52	
600	467.7	573.3	21.12	55.6	44.4	15 - 100
425	435	539.3	20.86	74.46	25.54	
300	384.3	430.8	9.3	85.76	14.24	5 to 70
150	420.5	480.9	12.08	97.84	2.16	0 - 15
75	326.9	330.1	0.64	98.48	1.52	
pan	297.6	304.7	1.42	99.9	0.1	

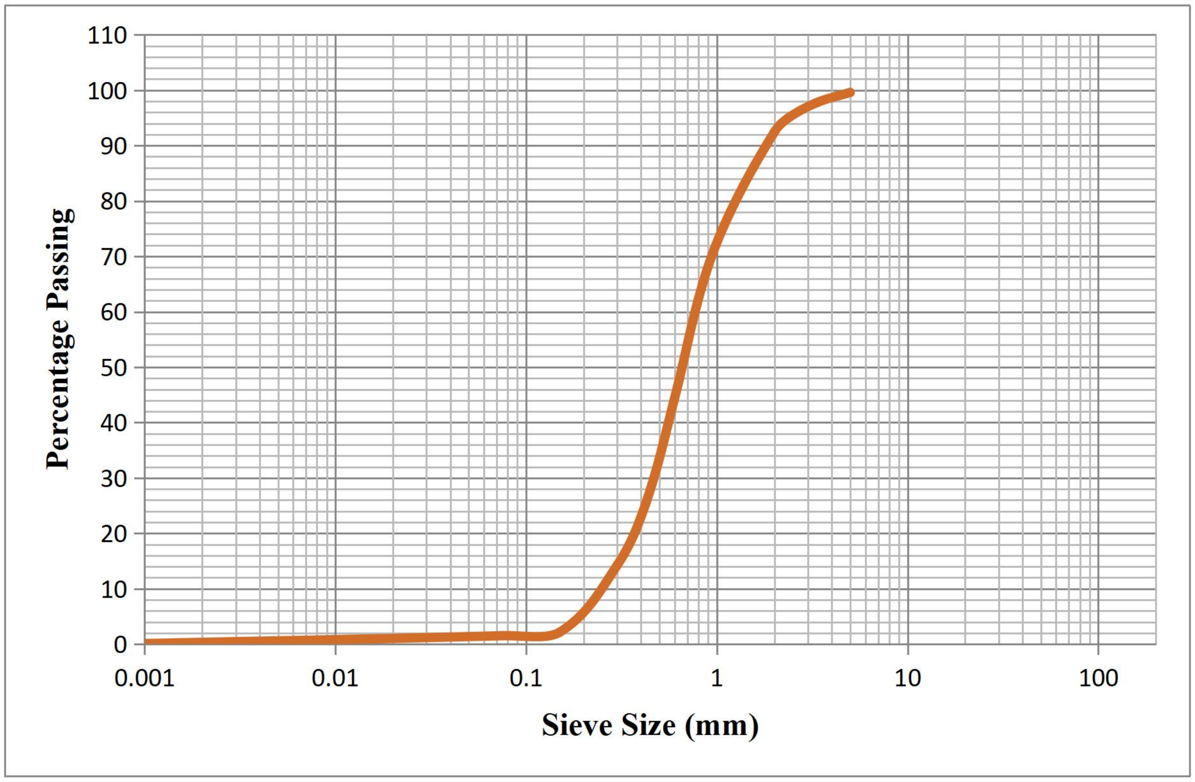


Figure 4.2: Particle size distribution curve for fine aggregate

4.2 Slump, Strength Properties and Modulus of Elasticity

4.2.1 Slump

Slump loss was used to examine the workability of each mix. The slump loss of all mixes was between 0 and 270 mm as presented in Table 4.9. A similar range of slump was recorded by Abbasi *et al.* (1985) 0 - 200 mm and Alhaji, (2016) 0 - 245 mm using similar w/c, ca/ta and ta/c ratios. The range of slump obtained covers the practical range of slump for normal weight concrete reported by Neville (2011). BS EN 206 - 1 (2006) categorised workability of concrete based on slump into five. No slump (So): Mix A11, A19, A21 A25 and C5 showed zero slump. These mixes were produced with low w/c and high ta/c ratio. This implies that the mix lack fine aggregate and the required amount of mixing water to produce adequate workability. Consequently, the mixes were stiff and harsh showing a deficiency of mixing water and a deficiency of cement. Low Slump (S1): Mix A2, A3, A4, A7, A15, A16, A17, A18, A20, A22, C2, C3, C4, C6, C7 and C9 had slump values corresponding to the low slump range (10 - 40 mm). This was attributed to the fact that the mixes contain high ca/ta ratio or were made with low w/c. This ultimately resulted in the production of partially stiff but workable mixes. Mixes in this range also indicated the highest range of compressive strength. Medium Slump (S2): Three mixes; A1, A13 and A27 fell in this category having a slump between 50 and 90 mm. These mixes were made using very low ta/c ratio which require more water for workability. The mixes also recorded high compressive strength values. High Slump (S3): None of the mixes prepared had slump values corresponding to this range (100 - 150 mm). Very High Slump (S4): Mixes with slump values in excess of 160 mm are characterised to have very high slump. Mix A5, A6, A8, A9, A10, A12, A14, A26 and C1 fell into this category. The mixes were prepared with a very high w/c ratio and very low ta/c ratio. This is an indication that the water was in excess of that which aids cohesion of the constituent materials.

Table 4.9: Slump and mechanical properties measured at 28days curing age

Run Order/ Mix ID	CA/TA	TA/C	w/c	Slump (mm)	Compressive Strength (N/mm^2)	Flexural Strength (N/mm^2)	Tensile Splitting Strength (N/mm^2)	Modulus of Elasticity (kN/mm^2)
1/A1	0.6	4.5	0.6	65	23.17	3.16	1.78	19.12
2/A2	0.55	6	0.5	10	27.51	4.71	2.06	21.66
3/A3	0.55	3	0.4	40	44.30	7.60	3.42	32.74
4/A4	0.55	6	0.6	25	26.93	4.67	2.05	20.37
5/A5	0.65	3	0.5	192	30.30	5.33	2.27	24.23
6/A6	0.55	3	0.5	195	26.74	4.60	2.04	20.97
7/A7	0.65	4.5	0.4	7	37.56	6.33	2.56	26.77
8/A8	0.65	4.5	0.6	178	24.89	4.00	1.95	19.68
9/A9	0.65	3	0.6	225	23.33	3.73	1.89	19.32
10/A10	0.55	4.5	0.6	178	22.96	2.93	1.76	19.29
11/A11	0.55	4.5	0.4	0	29.66	5.07	2.14	23.50
12/A12	0.6	3	0.5	190	34.37	5.87	2.44	25.79
13/A13	0.6	4.5	0.5	52	32.44	5.67	2.36	24.91
14/A14	0.55	3	0.6	270	25.78	4.40	2.02	20.88
15/A15	0.65	6	0.5	10	29.70	5.13	2.16	23.91
16/A16	0.65	3	0.4	26	41.63	6.53	2.71	31.29
17/A17	0.6	3	0.4	22	36.96	6.27	2.46	25.53
18/A18	0.55	4.5	0.5	8	32.96	5.80	2.41	24.63
19/A19	0.55	6	0.4	0	14.25	2.27	1.40	10.18
20/A20	0.65	6	0.6	3	28.52	4.80	2.09	21.27
21/A21	0.65	6	0.4	0	13.11	2.11	1.29	10.05
22/A22	0.6	6	0.5	2	30.44	5.53	2.33	24.99
23/A23	0.6	6	0.6	4	25.56	4.37	2.02	20.44
24/A24	0.6	4.5	0.4	3	28.22	4.80	2.08	23.21
25/A25	0.6	6	0.4	0	7.79	1.60	0.57	4.09
26/A26	0.6	3	0.6	230	24.53	3.96	1.93	19.61
27/A27	0.65	4.5	0.5	60	28.74	4.93	2.10	23.89
V1/C1	0.55	3.50	0.55	215	30.22	5.20	2.19	24.17
V2/C2	0.45	5.50	0.55	2	24.15	3.87	1.91	19.90
V3/C3	0.55	5.50	0.55	4.5	25.04	4.11	1.97	20.27
V4/C4	0.55	3.50	0.45	32	36.59	6.13	2.45	25.91
V5/C5	0.45	5.50	0.45	0	13.63	2.13	1.36	10.27
V6/C6	0.55	5.50	0.45	2	25.48	4.27	1.99	20.20
V7/C7	0.65	5.00	0.40	6	23.26	3.20	1.85	19.04
V8/C8	0.65	5.00	0.60	154	26.30	4.44	2.04	20.97
V9/C9	0.65	5.00	0.50	33	30.22	5.27	2.25	23.31

4.2.2 Compressive strength

The compressive strength of all specimens made with various combination of constituents were determined after curing by full immersion for 28 days. The compressive strength of concrete is dependent on factors such as water-cement ratio, cement type and strength, material quality and quality control techniques. It also depends to a great extent on the quality of cement paste, type of aggregate and the transition zone between the aggregate and cement paste (Rocco and Elices, 2009; Neville 2011; Neville and Brooks, 2001; Abdullahi, 2012). The compressive strength recorded was between 7.79 and 44.30 N/mm^2 as shown in Table 4.9. Although four (A19, A21, A25 and C5) mixes fell below the C15 grade of concrete (14.25, 13.11, 7.79 and 13.63 N/mm^2 respectively), all other mixes recorded compressive strength well above the C20 grade (22.96 - 44.30 N/mm^2). Mix A19, A21, A25 and C5 is discouraged for structural application while other mixes are suitable for various types of structural use such as construction of slabs, beams, columns, footings and pre-stressed concrete elements depending on their actual designated grade. It was, however, observed that mixes A19, A21, A25 and C5 indicated low compressive strength because they were made with low W/C but high ca/ta and high ta/c ratios. High ta/c ratio implies that low cement content was used and high ca/ta ratio implies that the mixes contain high amount of fine aggregates, which will normally require high water and cement content, in order to achieve any reasonable strength and workability for structural application. The mixes were extremely harsh and stiff as was observed from their slump values. Therefore, the combination of constituent materials leading to the production of the mixes should be avoided. It is a well-established fact that the lower the w/c ratio, the higher the compressive strength of concrete. Compressive strength greater than 40 N/mm^2 was recorded for Mix A3 and A16 specimens. These mixes were prepared with high cement content corresponding to low ta/c ratio, low w/c ratio and high ca/ta ratio corresponding to high coarse aggregate content. This is a clear indication that the properties of the constituent materials can further be engineered to produce concrete of considerable high strength without necessarily using mineral or chemical admixtures. The failure pattern and failure surface of one of the test specimens is shown in Appendix B. It was observed that the coarse aggregate was the factor contributing most to the failure of the specimens as most of the aggregate sheared or broke into pieces after crushing. This was the case for almost all the other specimens.

4.2.3 Flexural strength

Although the 28-day compressive strength of concrete is the most desirable property used in the design of concrete structural elements, other properties are also important so as to study the behavior of the element under various loading conditions. Flexural strength otherwise known as the modulus of rupture, is a measure of the response of prismatic concrete beams to vertical forces. A typical range of flexural strength of concrete reported by Alhaji (2016), lies between 2 N/mm^2 and 7 N/mm^2 inclusively. The flexural strength obtained herein encompass 1.6 N/mm^2 to 7.6 N/mm^2 as shown in Table 4.9. Only mix A25 did not fall within the prescribed range. All other mixes were within the specified range. The pattern of strength increase or decrease in flexural strength based on the mix ingredients were similar to the compressive strength results. The failure pattern and failure surface of a representative specimen is shown in Appendix C. The aggregate surface is also seen as the most susceptible failure plane since it is the most stressed failure surface of the concrete and closest to the applied loads.

4.2.4 Splitting tensile strength

Concrete is a composite material with low tensile capacity. The tensile strength of concrete can be measured directly or indirectly. The tensile strength of concrete is a function of the strength and type of aggregates (Neville, 2011; Sallal *et al.,* 2018). Since this research herein is based on the use of naturally occurring coarse aggregates, it became necessary to evaluate the tensile behavior of the concrete produced from these aggregates. The tensile splitting strength obtained was between 0.57 - 3.42 N/mm^2. Although mix A19, A21, A25 and C5 recorded very low splitting tensile strength values. This was also the case in the compressive strength of those mixes. All other mixes indicated values between 1.76 and 3.42 N/mm^2 as shown in Table 4.7. The splitting tensile strength obtained at 28 days of curing for 20 different mixes by Alhaji (2016) using the same coarse aggregates and similar constituents was between 0.72 and 2.62 N/mm^2. Furthermore, results obtained by Sallal *et al.* (2018), SagarTanwani (2016), Kanawade *et al.* (2014), Joseph and Maurice (2012) and Ali *et al.* (2018) were between 1.85 and 4.96 N/mm^2. The results obtained using BNG are, however, within this range. The failure pattern and failure surface are depicted in Appendix D.

4.2.5 Modulus of elasticity

In order to avoid excessive deformations while maintaining acceptable serviceability requirements when designing concrete elements, the modulus of elasticity of normal weight concrete must be between 18 - 34 kN/mm^2 for 28 day compressive strength and between 20 - 40 N/mm^2 as specified in BS 8110 - 2 (1997). The modulus of elasticity recorded for all mixes was between 4.09 - 32.74 kN/mm^2 as presented in Table 4.9. Mix A19, A21, A25 and C5 indicated the lowest modulus of elasticity between 4.09 and 10.05 kN/mm^2. Other mixes indicated between 19.04 kN/mm^2 and 32.74 kN/mm^2, which were well within the range for normal weight concrete specified by BS 8110 (1997). Relating the modulus of elasticity to the compressive strength, it was observed that mix A19, A21, A25 and C5 indicated compressive strength less than grade C15. The reasons for the low compressive strength recorded by these mixes are therefore in line with the reasons for their low elastic modulus values.

4.3 Artificial Neural Network (ANN) Models

Since there is no predetermined rule guiding the use of a particular ANN architecture that will adequately perform the required prediction for the ANN models, several ANN architectures from 1 to 50 neurons with a multiple of 2 neurons in the hidden layer per iteration were tried, based on the premise of Bandara (2013). Tansig and logsig activation function were tried for each of the architectures in each case.

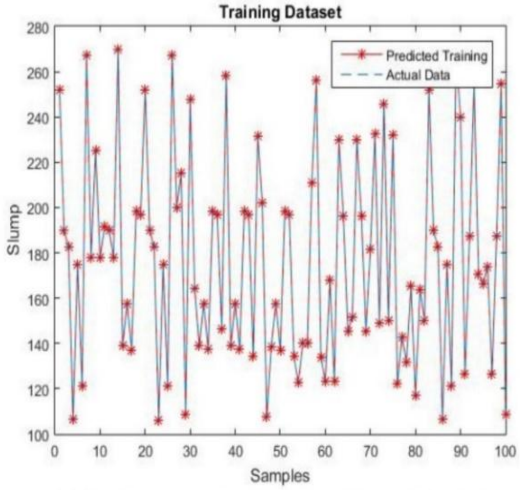
4.3.1 ANN slump model

The performance metrics for the cases 1 and 2 slump models with tangent sigmoid and logistic sigmoid activation functions in the training, validation and testing phase are as given in Table 4.10. It can be observed that there exists a significant difference in the performance of the models based on the MSE and RMSE results. Although the regression (R) for both models were similar. The case 1 model with a tansig activation function indicated the least MSE values of 0.0014, 0.1268, 0.0015 and RMSE values of 0.0375, 0.3560, 0.0393 in the training, validation and testing phase respectively. A better accuracy when compares to MSE of 0.0149, 0.3341, 0.0094 and RMSE of 0.1219, 0.5780, 0.0972 was indicated by the case 2 model in the training, validation and testing phase respectively. Low MSE and RMSE values proves that the difference between experimental results and the model output is trivial. The dynamic range of the tangent sigmoid activation function of (-1, 1) as compared to the logistic sigmoid range (0,1) accounts for why the case 1 model provides better performance. Furthermore, the min-max data normalisation approach adopted to transform inputs to a uniform scale between -1 and +1 is suitable for tansig activation functions. This shows that the type of normalization technique as well as type of activation function affects the performance of ANN slump model for concrete containing Bida natural gravel.

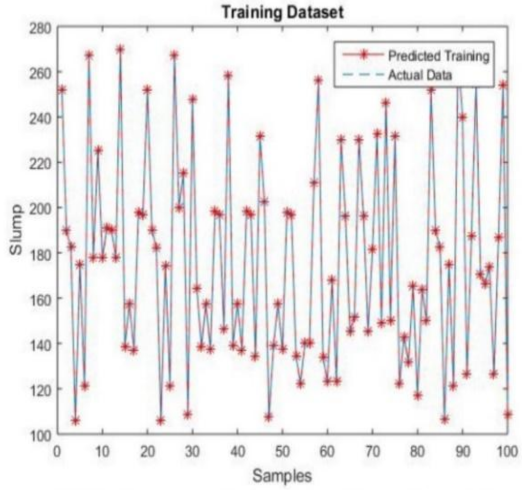
Table 4.10: Performance result for cases 1 and 2 models (Slump)

Performance	MSE	RMSE	R	Hidden layer function/Architecture
Training	0.0014	0.0375	1.0000	Tansig/5-89-1
	0.0149	0.1219	1.0000	Logsig/5-75-1
Validation	0.1268	0.3560	1.0000	Tansig/5-89-1
	0.3341	0.5780	0.9999	Logsig/5-75-1
Testing	0.0015	0.0393	1.0000	Tansig/5-89-1
	0.0094	0.0972	1.0000	Logsig/5-75-1

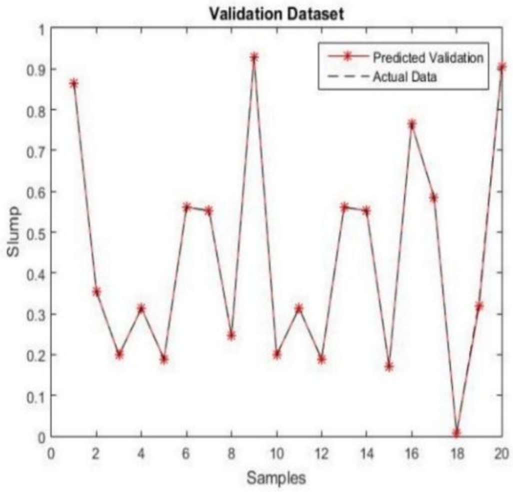
In addition to the MSE and RMSE values, the regression (R) was used to judge the accuracy of the cases 1 and 2 models. High values of R depict a high goodness of fit of the model result to the actual experimental data. Nevertheless, the R metrics is limited to 1. Based on results presented in Table 4.10, a R of 1 signifying a perfect goodness of fit was recorded in the training, validation and testing phase for the cases 1 and 2 models except for the logsig activation function, which indicated a regression, R, of 0.9999 in the validation phase. This further confirms that the case 1 model possesses superior performance to the case 2 model. The performance output for the training, validation and testing phase are presented in Figure 4.6 and 4.7. From the Figures, it was observed that the actual experimental results fitted almost perfectly with the model outputs in the training, validation and testing phase for the cases 1 and 2 models. Although a negligible deviation exists in the validation result of the model with logsig activation function between the 18^{th} and 20^{th} data points. This explains why it indicated a R of 0.9999 in the validation phase. The R values obtained exceeds R of 0.937 reported by Alhaji (2016) using statistical modelling approach to model slump of concrete containing Bida natural coarse aggregate. Thus, the case 1 model is the best and selected model for predicting the slump of concrete using Bida natural gravel as coarse aggregates.



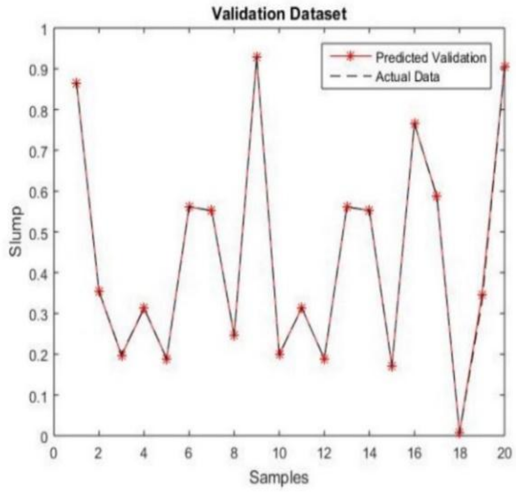
(a) Performance for Training Phase (Tansig)



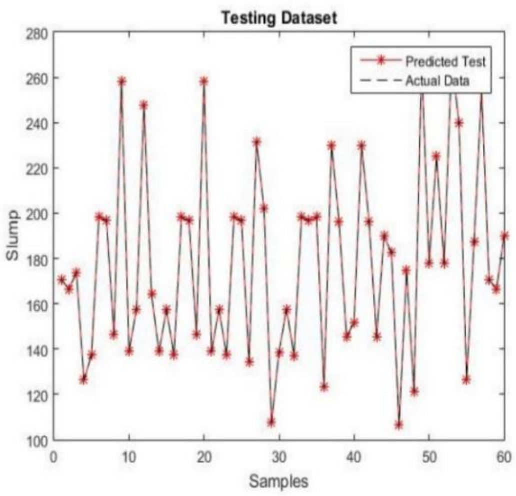
(b) Performance for Training Phase (Logsig)



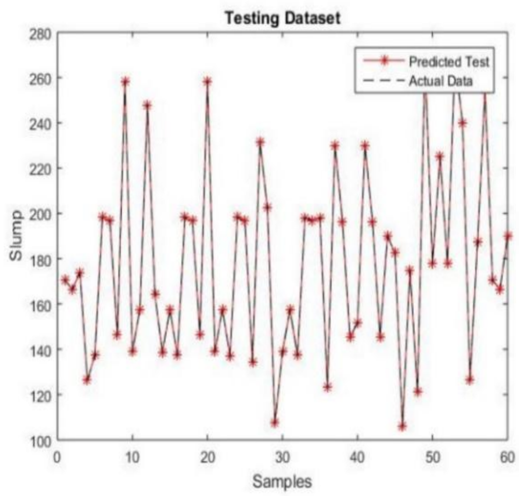
(c) Performance for Validation Phase (Tansig)



(d) Performance for Validation Phase (Logsig)

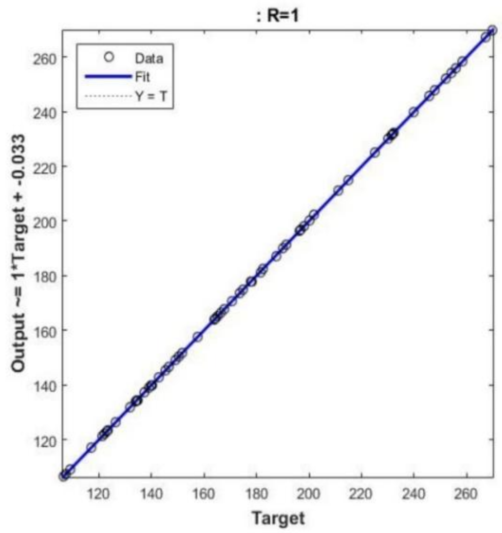


(e) Performance for Testing Phase (Tansig)

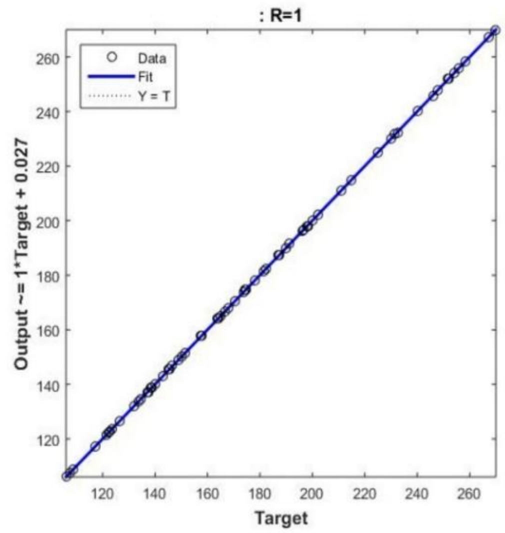


(f) Performance for Testing Phase (Logsig)

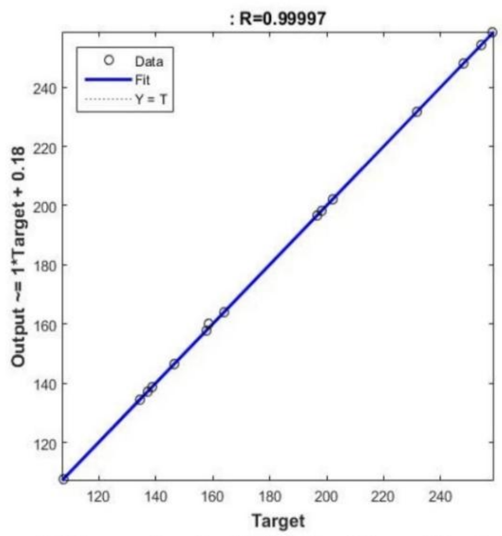
Figure 4.6: Relationship of actual to predicted results for cases 1 and 2 (slump model).



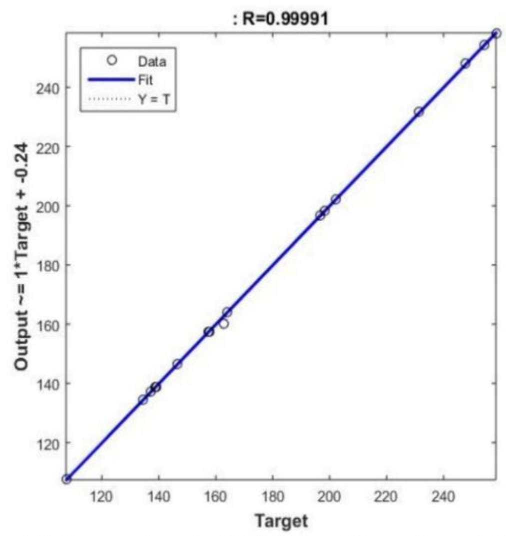
(a) Regression for Training Phase (Tansig)



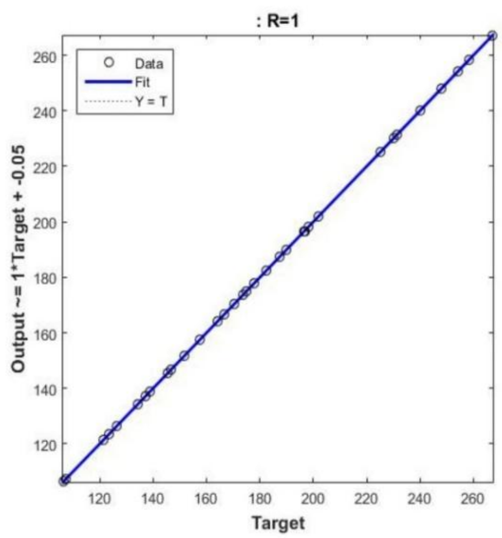
(b) Regression for Training Phase (Logsig)



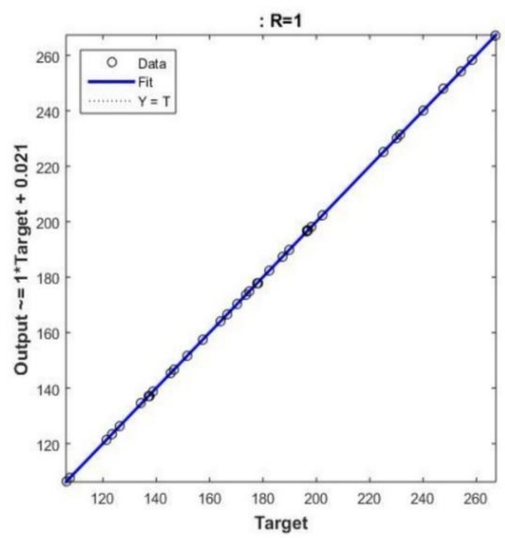
(c)Regression for Validation Phase (Tansig)



(d) Regression for Validation Phase (Logsig)



(e) Regression for Testing Phase (Tansig)



(f) Regression for Testing Phase (Logsig)

Figure 4.7: Regression result for cases 1 and 2 slump model.

The weights and bias of the ANN for the case 1 slump model with the least MSE, RMSE and highest R in the training, validation and testing phase are presented in Appendix E. Accordingly, the model equation for the selected slump model (case 1) is given in Equation 4.1.

$$\boldsymbol{\xi} = \mu(\sum_{i=1}^{n} wij\,.\,\boldsymbol{\phi} + 0.3203 \qquad (4.1)$$

4.3.2 ANN compressive strength model

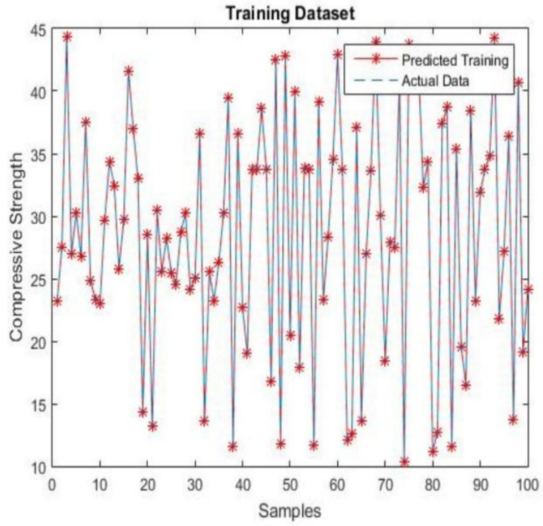
Performance parameters obtained for cases 1 and 2 compressive strength models are presented in Table 4.11. The parameters were analogous with the trend obtained in the slump model for cases 1 and 2.

Table 4.11: Performance result for cases 1 and 2 models (compressive strength)

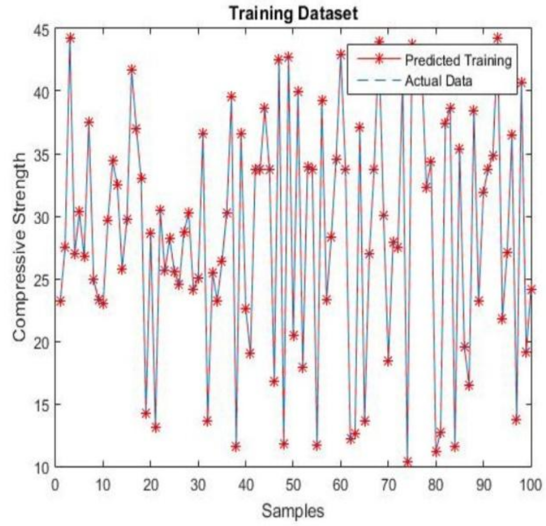
Performance	MSE	RMSE	R	Hidden layer function/Architecture
Training	$3.2971xe^{-04}$	0.0182	1.0000	Tansig/5-69-1
	$6.4206xe^{-04}$	0.0253	1.0000	Logsig/5-89-1
Validation	$7.2308xe^{-04}$	0.0269	1.0000	Tansig/5-69-1
	0.0219	0.1480	0.9999	Logsig/5-89-1
Testing	$2.4230xe^{-04}$	0.0156	1.0000	Tansig/5-69-1
	$5.7678xe^{-04}$	0.0240	1.0000	Logsig/5-89-1

It was observed that MSE and RMSE obtained in the case 1 model were much lower than the case 2 model in the training, validation and testing phase. The case 1 model indicated MSE of $3.2971xe^{-04}$, $7.2308xe^{-04}$, $2.4230xe^{-04}$ and RMSE 0.0182, 0.0269, 0.0156 in the training, validation and testing phase. It is revealing that the case 2 model with MSE of $6.4206xe^{-04}$, 0.0219, $5.7678xe^{-04}$ and RMSE of 0.0253, 0.1480, 0.0240 in the training, validation and testing phase respectively, presents lower accuracy to the case 1 model. An indication that the case 1 model presents the most negligible error between the experimental compressive strength and the model results. The low RMSE recorded also signifies that the residuals are much closer to the fitted line as shown in Figures 4.8 and 4.9. Similar to the slump model, the dynamic range of the tangent sigmoid activation function of (-1, +1) as compared to the logistic sigmoid range (0, +1) accounts for why the case 1 model provides superior performance. Moreover, the min-max data normalisation approach used to transform inputs to a uniform range between -1 and +1 is suitable for tansig activation functions and this shows that the type of normalization technique as well as the type of activation function affects the performance of ANN compressive strength models for concrete containing Bida natural gravel. Regression (R) was further used to examine the precision of the compressive strength models. R value of 1 was recorded by the case 1 model in the training, testing and validation phase. The case 2 model also recorded R value of 1 in the training and testing phase, but 0.9999 in the validation phase. Based on the result presented in Figure 4.8, a perfect goodness of fit was recorded in the training, validation and testing phase for the cases 1 and 2 models. The R values exceeds R of 0.998 reported by Alhaji (2016) using statistical modelling approach to model compressive strength of concrete containing Bida natural coarse aggregates. The case 1 model is thus selected as the best model. The weights and bias of the ANN for the selected case 1 model with the least MSE, RMSE and highest R in the training, validation and testing phase are presented in Appendix F. Accordingly, the model equation for the selected compressive strength model (case 1) is given in Equation 4.2.

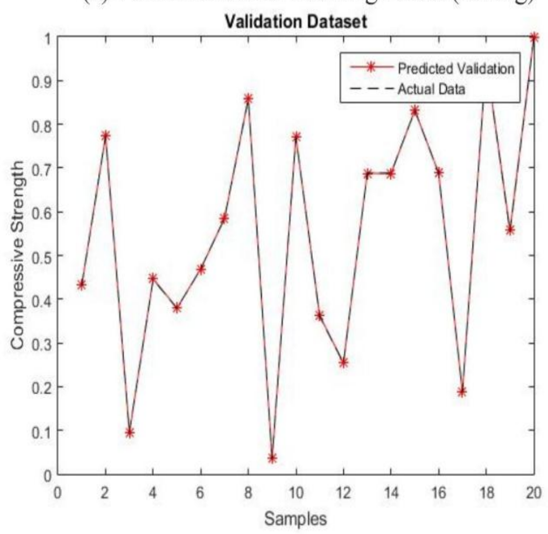
$$\boldsymbol{\xi} = \mu(\textstyle\sum_{i=1}^{n} wij \,.\, \boldsymbol{\phi} + 0.2429 \qquad (4.2)$$



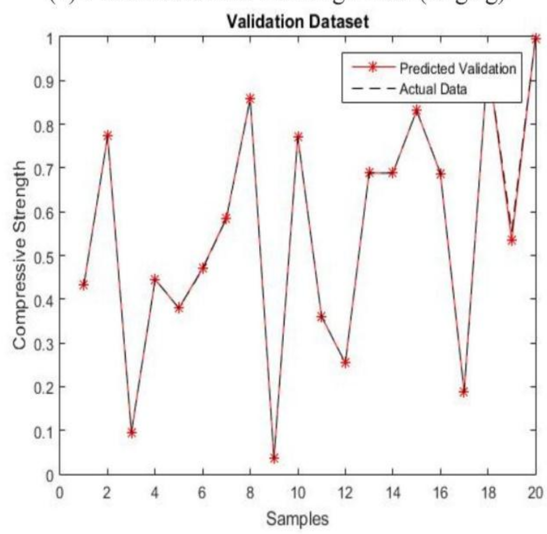
(a) Performance for Training Phase (Tansig)



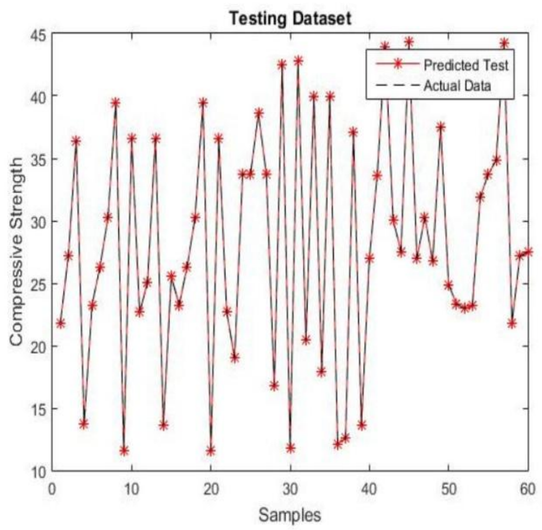
(b) Performance for Training Phase (Logsig)



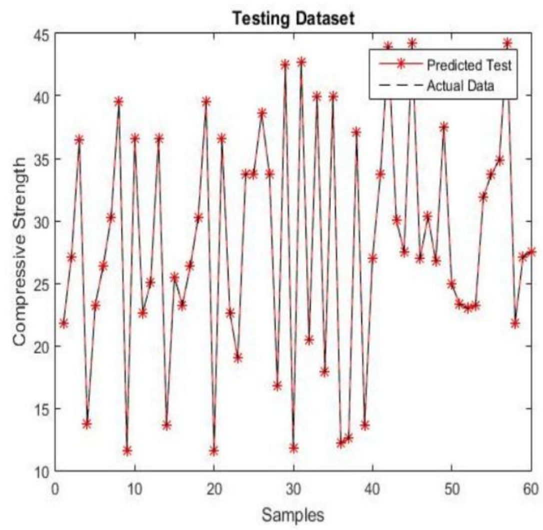
(c) Performance for Validation Phase (Tansig)



(d) Performance for Validation Phase (Logsig)

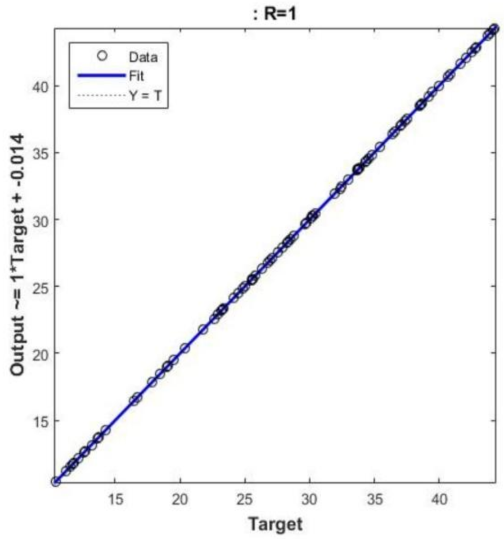


(e) Performance for Testing Phase (Tansig)

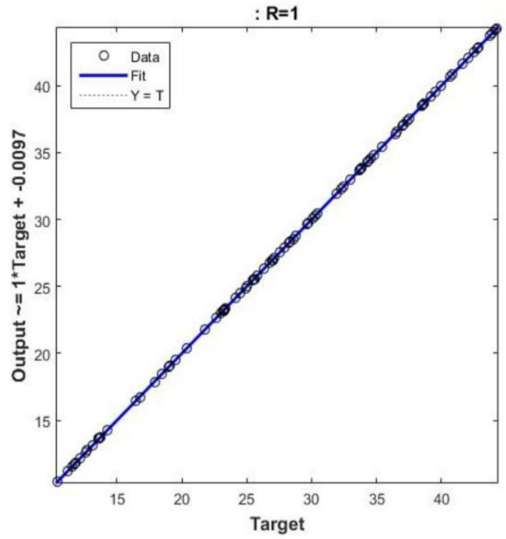


(f) Performance for Testing Phase (Logsig)

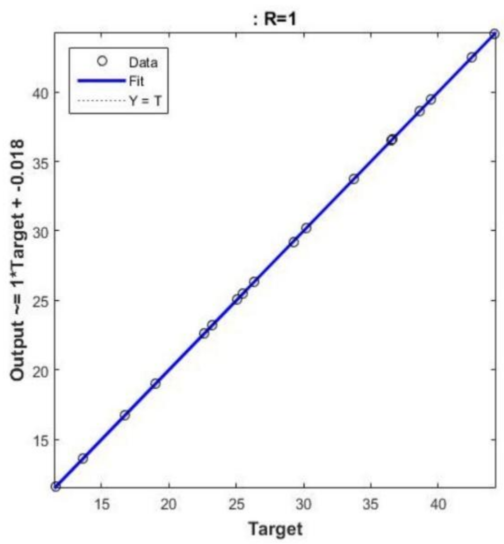
Figure 4.8: Relationship of actual to predicted results for cases 1 and 2 (compressive strength model).



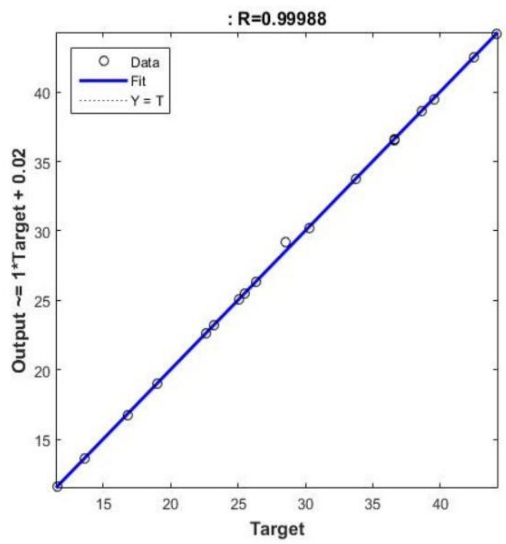
(a) Regression for Training Phase (Tansig)



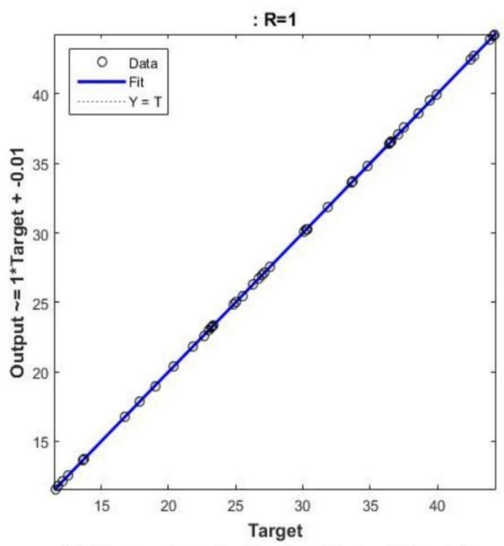
(b) Regression for Training Phase (Logsig)



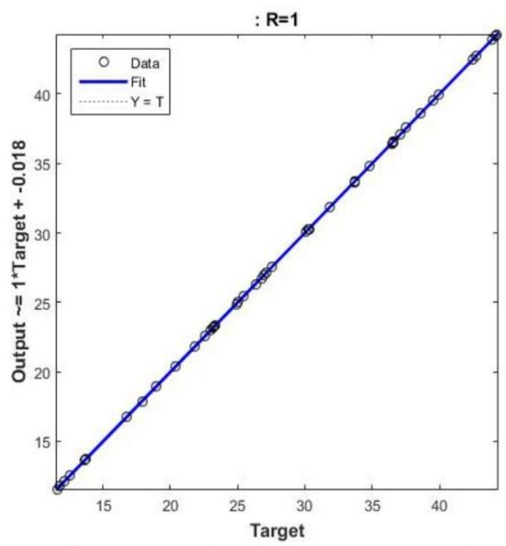
(c) Regression for Validation Phase (Tansig)



(d) Regression for Validation Phase (Logsig)



(e) Regression for Testing Phase (Tansig)



(f) Regression for Testing Phase (Logsig)

Figure 4.9: Regression result for cases 1 and 2 compressive strength models.

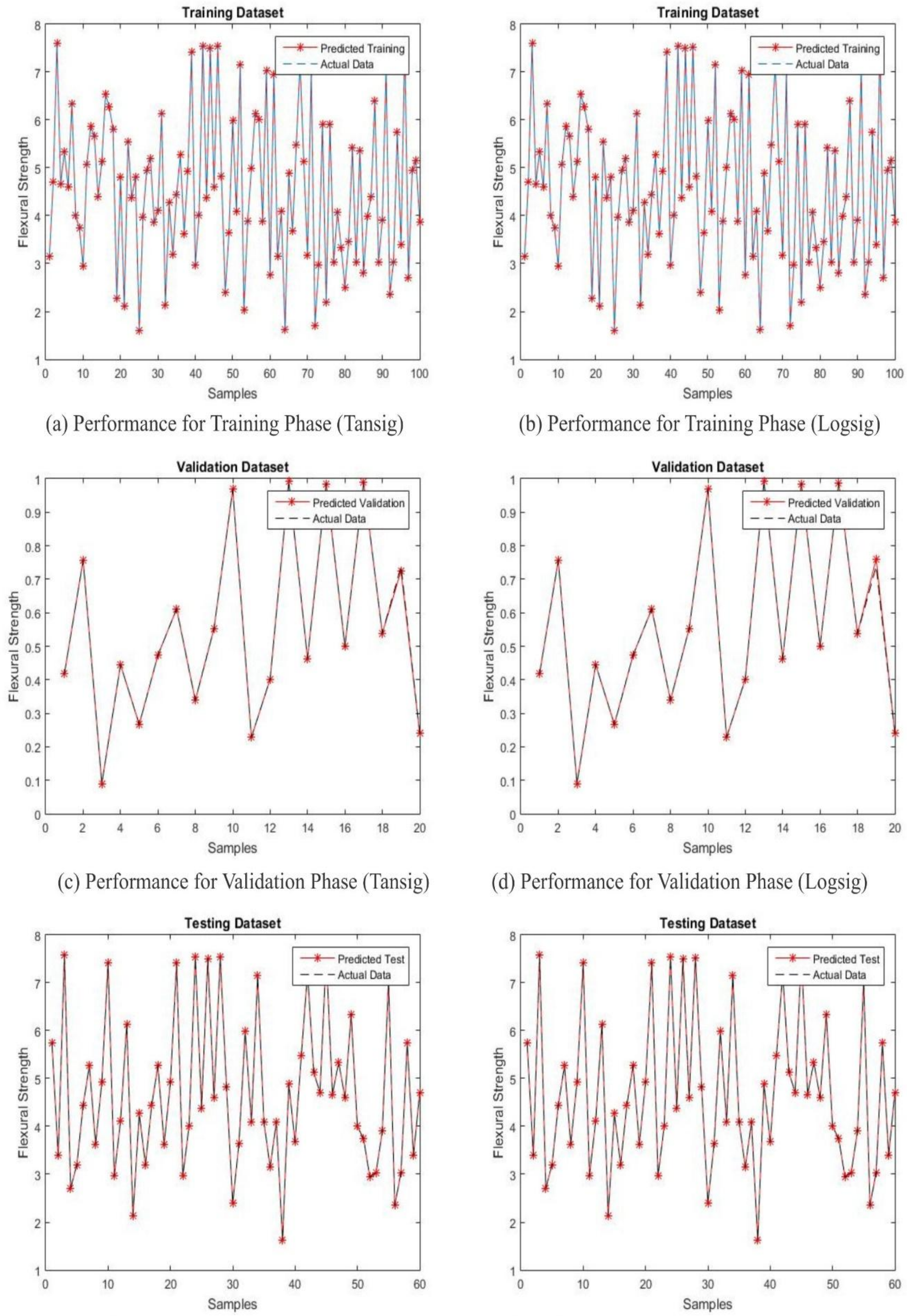
4.3.3 ANN flexural strength model

The performance metrics obtained for case 1 and case 2 models are presented in Table 4.12. It was observed that the case 1 model indicated MSE and RMSE of 1.6754xe^{-07}, 3.0976xe^{-04}, 1.6223e^{-07} and 4.0932xe^{-04}, 0.0176, 4.0278xe^{-04} respectively, while the case 2 model indicated a MSE and RMSE of 6.0418xe^{-10}, 8.7042xe^{-04}, 6.1359xe^{-10} and 2.4580xe^{-05}, 0.0295, 2.4771xe^{-05} during the training validation and testing phase respectively. A better performance when compared with the case 1 model. In the validation phase, however, the case 1 model indicated a slightly higher MSE and RMSE than the case 2 model. This emphasises that the case 2 model presents the most negligible error between the experimental compressive strength and the model results in the training and testing phase. A small RMSE value obtained in the training and testing phase signify that the residuals are much closer to the fitted line as shown in Figures 4.10 and 4.11. Contrary to the slump and compressive strength models, the case 2 model with logistic sigmoid activation function gave the best performance. This was the case, because the range of values obtained after normalisation of the data sets for flexural strength converges quickly in the neighborhood of 0 and 1. This range is particularly adapted to logistic functions with saturation values of 0 and 1. Furthermore, the optimal result (case 2 model) recorded 91 neurons in the hidden layer, while the case 1 model indicated optimal result with 81 hidden neurons. The regression values of the case 2 model gave R value of 1 in the training and testing phase but an R value of 0.9998 in the validation phase as depicted in Figure 4.11. When compared to R value of 0.998 obtained by Alhaji (2016) for statistical model for flexural strength of concrete containing Bida natural coarse aggregate, the ANN flexural strength model can be said to possess a better prediction capacity based on the MSE, RMS and R metrics. The case 2 model is therefore presented as the best ANN model for predicting the flexural strength of concrete containing Bida natural gravel. The weights and bias of the ANN for the selected case 2 model with the least MSE, RMSE and highest R in the training, validation and testing phase are presented in Appendix G. Consequently, the flexural strength model equation for the selected model (case 2) is given in Equation 4.3.

$$\boldsymbol{\psi}_{\text{output}} = \mu\left(\sum_{i=1}^{n} wij \,.\, \nabla - 0.0299\right) \quad (4.3)$$

Table 4.12: Performance result for cases 1 and 2 models (flexural strength)

Performance	MSE	RMSE	R	Hidden layer function/Architecture
Training	1.6754xe^{-07}	4.0932xe^{-04}	1.0000	Tansig/5-81-1
	6.0418xe^{-10}	2.4580xe^{-05}	1.0000	Logsig/5-91-1
Validation	3.0976xe^{-04}	0.0176	0.9999	Tansig/5-81-1
	8.7042xe^{-04}	0.0295	0.9998	Logsig/5-91-1
Testing	1.6223e^{-07}	4.0278xe^{-04}	1.0000	Tansig/5-81-1
	6.1359xe^{-10}	2.4771xe^{-05}	1.0000	Logsig/5-91-1



(a) Performance for Training Phase (Tansig)

(b) Performance for Training Phase (Logsig)

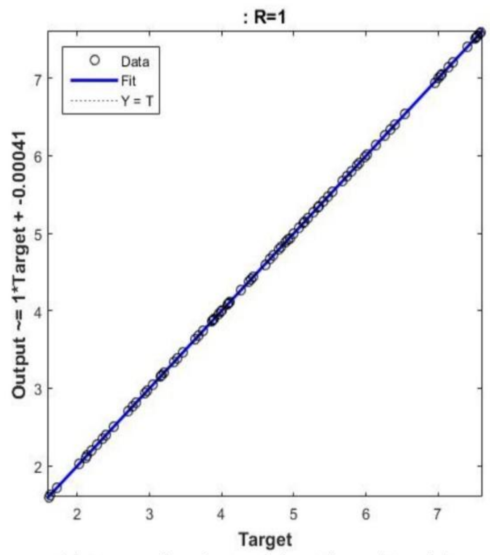
(c) Performance for Validation Phase (Tansig)

(d) Performance for Validation Phase (Logsig)

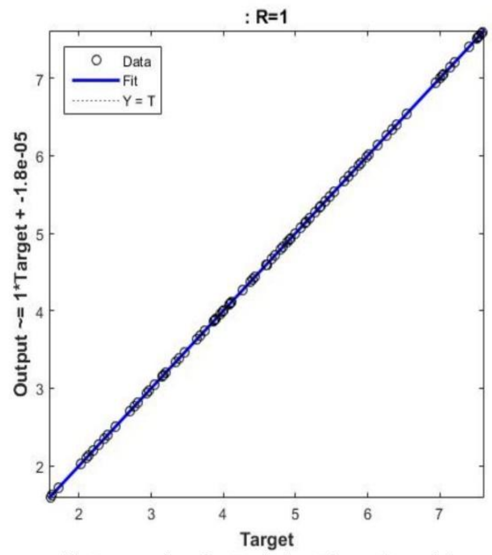
(e) Performance for Testing Phase (Tansig)

(f) Performance for Testing Phase (Logsig)

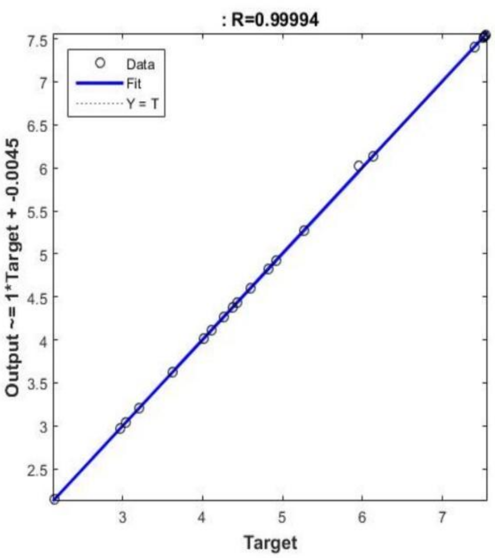
Figure 4.10: Relationship of actual to predicted results for cases 1 and 2 (flexural strength models).



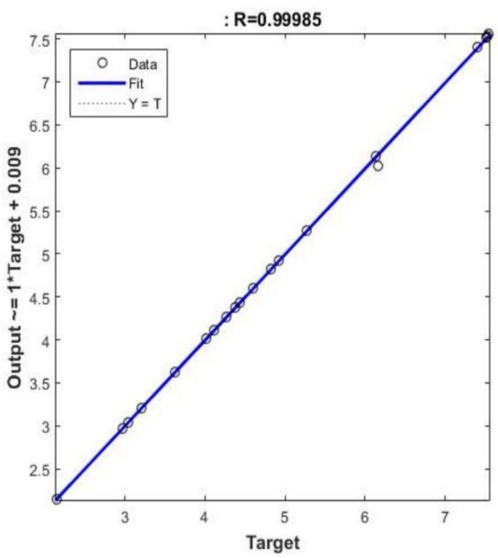
(a) Regression for Training Phase (Tansig)



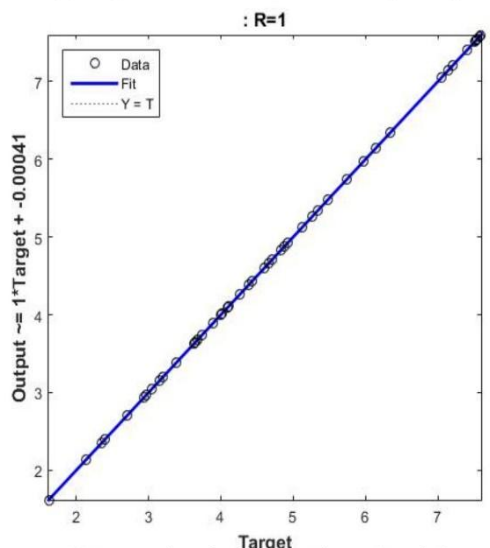
(b) Regression for Training Phase (Logsig)



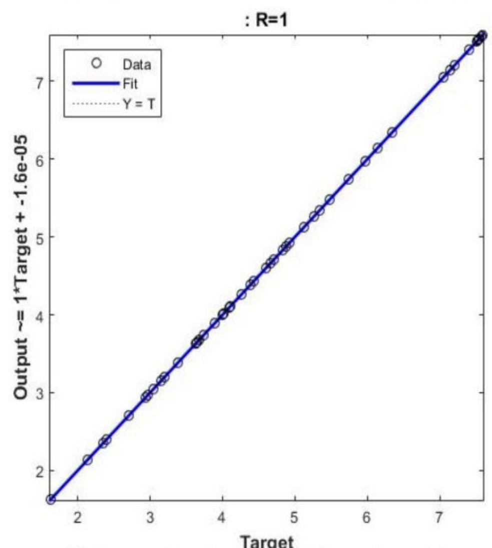
(c) Regression for Validation Phase (Tansig)



(d) Regression for Validation Phase (Logsig)



(e) Regression for Testing Phase (Tansig)



(f) Regression for Testing Phase (Logsig)

Figure 4.11: Regression result for cases 1 and 2 flexural strength model.

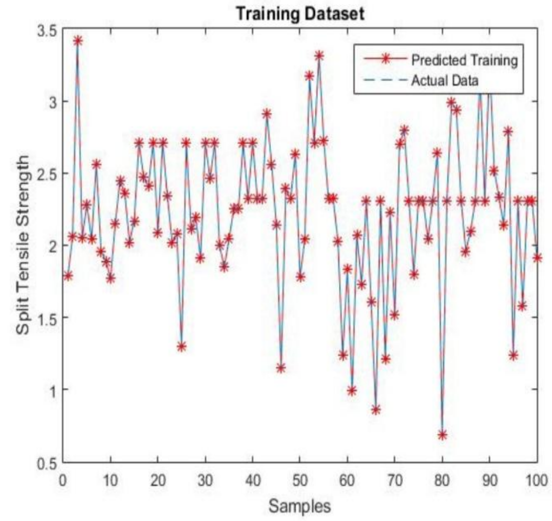
4.3.4 ANN splitting tensile strength model

Table 4.13 shows the summary of the performance obtained for cases 1 and 2 of split tensile strength, ANN model. The case 1 model indicated substantially lower MSE and RMSE values and higher R value in the training, validation and testing stage than the case 2 model. The case 1 model showed MSE and RMSE of 2.8449xe^{-09}, 6.6054xe^{-04}, 2.7093xe^{-09} and 5.3338xe^{-05}, 0.0257, 5.2050xe^{-05} respectively in the training, validation and testing phase. A much better performance to the case 2 model which recorded MSE and RMSE of 0.0025, 0.0056, 0.0016 and 0.0499, 0.0752, 0.0406 respectively in the training, validation and testing phase. Lower MSE value depicts that the error between the actual experimental result and the model output is very small. Low RMSE value on the other hand accounts for the closeness of the residual to the fitted line as can be seen in Figures 4.12 and 4.13. From Figure 4.13, it is evident that the actual data fits closely to the model data in the training, validation and testing stage with high R value of 1, 0.9981 and 1 in the training, validation and testing phase signifying high goodness of fit. Comparing the R value of the case 1 model to 0.937 R value reported by Alhaji (2016), the case 1 model with R value of 1 can be said to possess better precision. The case 1 model displayed better performance due to the range of tansigmoid activation function and the min - max normalisation technique adopted, which operates on the data range between -1 and +1. Consequently, the case 1 model with tansigmoid activation function is selected as the best model for predicting the split tensile strength of concrete using Bida natural gravel as aggregate. The weights and bias of the ANN for the selected case 1 model with the least MSE, RMSE and highest R in the training, validation and testing phase are presented in Appendix H. Consequently, the split tensile strength model equation for the selected model (case 1) is given in Equation 4.4.

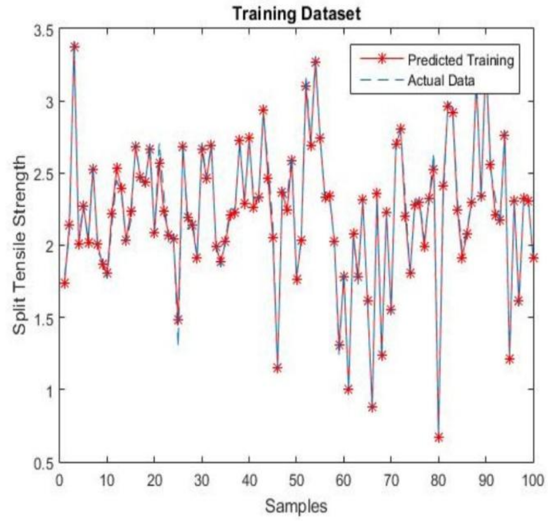
$$\boldsymbol{\xi} = \mu(\textstyle\sum_{i=1}^{n} wij\,.\,\boldsymbol{\phi} + 0.1711 \qquad (4.4)$$

Table 4.13: Performance result for cases 1 and 2 models (split tensile strength)

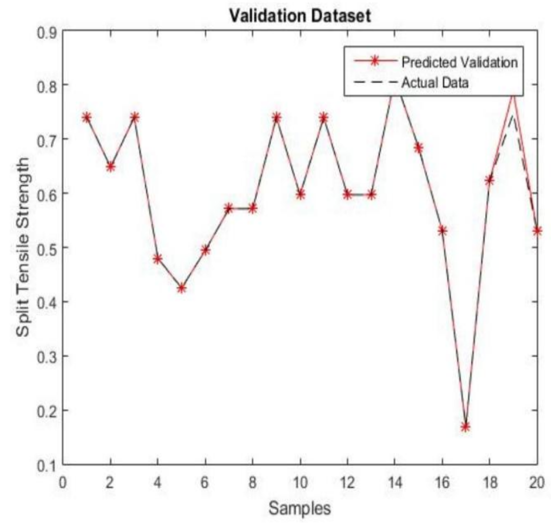
Performance	MSE	RMSE	R	Hidden layer function/Architecture
Training	2.8449xe^{-09}	5.3338xe^{-05}	1.0000	Tansig/5-91-1
	0.0025	0.0499	0.9955	Logsig/5-27-1
Validation	6.6054xe^{-04}	0.0257	0.9981	Tansig/5-91-1
	0.0056	0.0752	0.9842	Logsig/5-27-1
Testing	2.7093xe^{-09}	5.2050xe^{-05}	1.0000	Tansig/5-91-1
	0.0016	0.0406	0.9968	Logsig/5-27-1



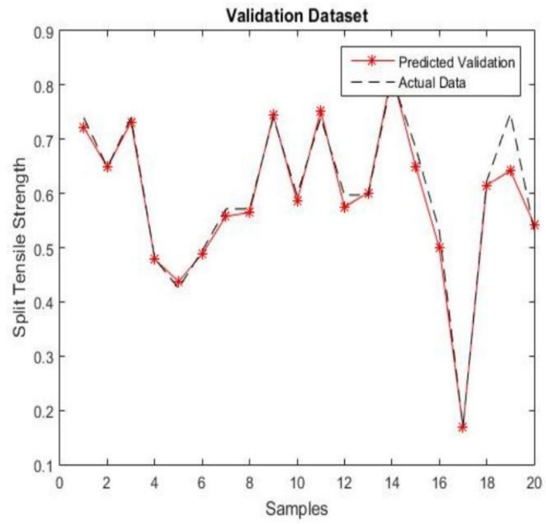
(a) Performance for Training Phase (Tansig)



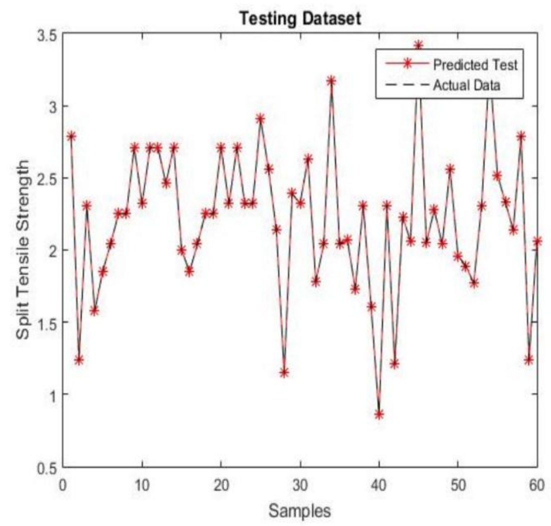
(b) Performance for Training Phase (Logsig)



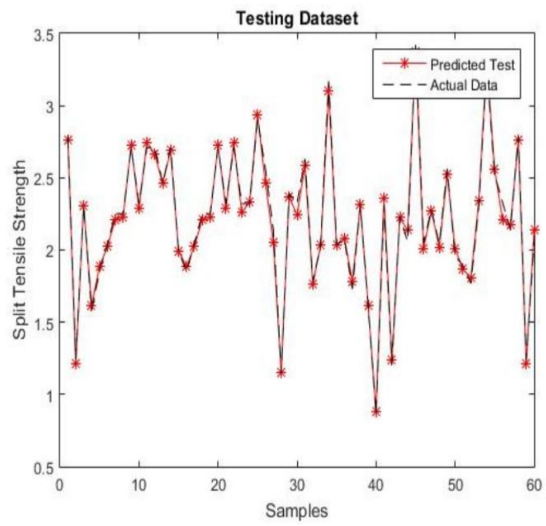
(c) Performance for Validation Phase (Tansig)



(d) Performance for Validation Phase (Logsig)

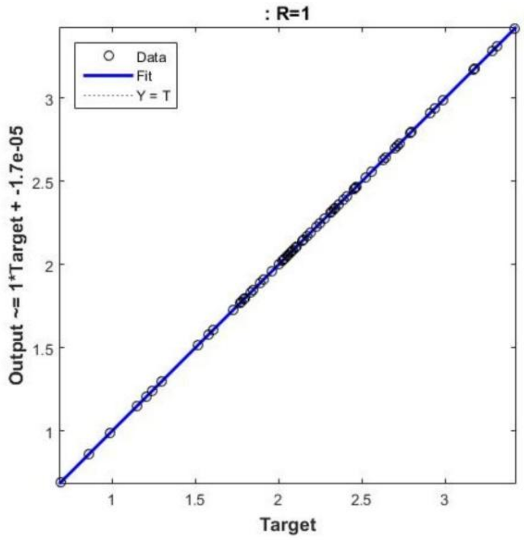


(e) Performance for Testing Phase (Tansig)

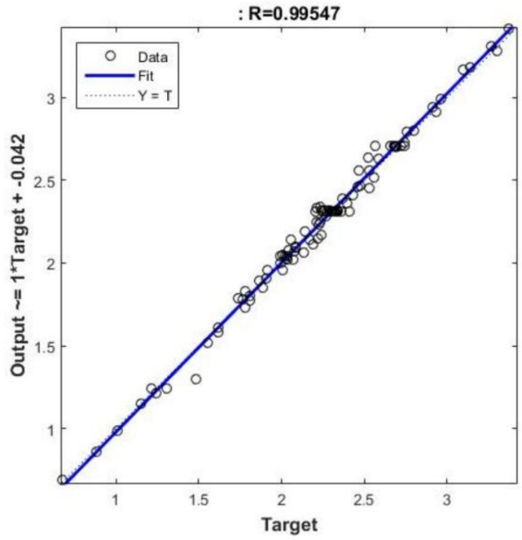


(f) Performance for Testing Phase (Logsig)

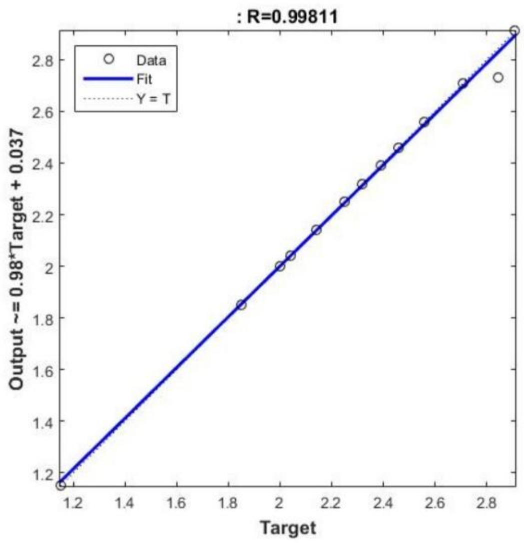
Figure 4.12: Relationship of actual to predicted results for cases 1 and 2 (flexural strength model).



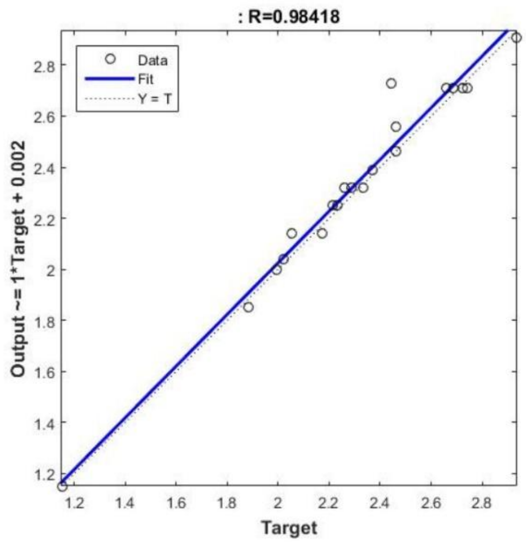
(a) Regression for Training Phase (Tansig)



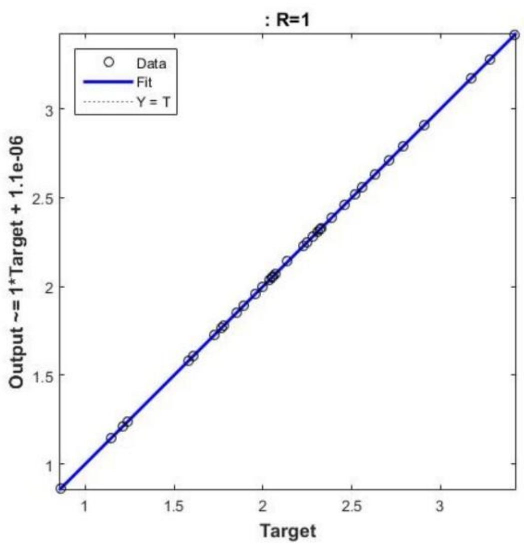
(b) Regression for Training Phase (Logsig)



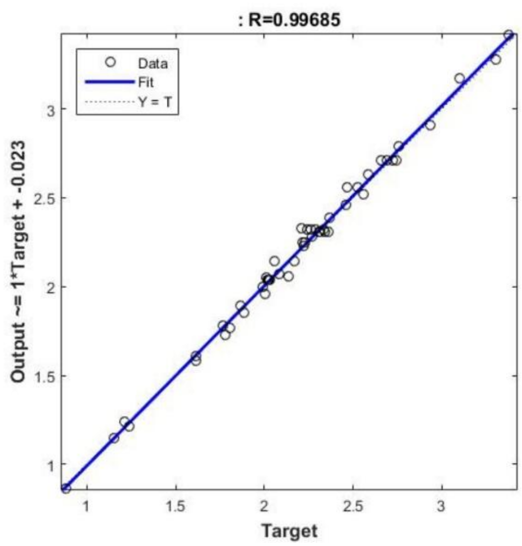
(c) Regression for Validation Phase (Tansig)



(d) Regression for Validation Phase (Logsig)



(e) Regression for Testing Phase (Tansig)



(f) Regression for Testing Phase (Logsig)

Figure 4.13: Regression result for cases 1 and 2 flexural strength model.

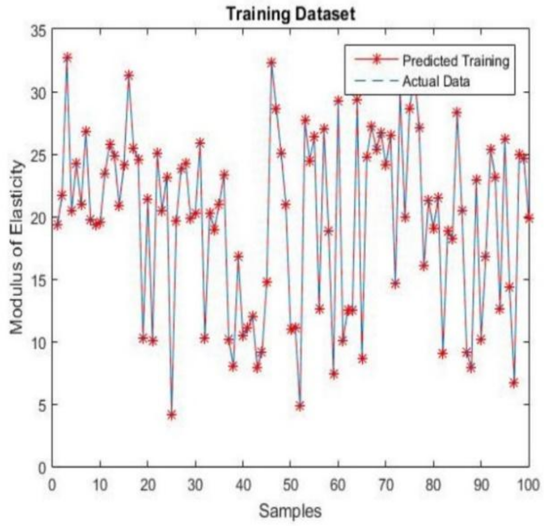
4.3.5 ANN modulus of elasticity model

Summary of the performance recorded by the cases 1 and 2 modulus of elasticity models are presented in Table 4.14. The case 1 model indicated MSE of 0.006, 1.1110 and 1.1110 in the training, validation and testing phase respectively. A less superior performance when compared to the case 2 model, which recorded MSE of $3.961xe^{-07}$, 3.0398 and $3.9310xe^{-07}$ in the training, validation and testing phase respectively. This shows that the case 2 model presents the smallest amount of error between the experimental data and the model output. The case 2 model showed higher RMSE of $6.2941xe^{-04}$ and $6.2698xe^{-04}$ in the training and testing phase respectively. In the validation phase of the case 2 model, RMSE of 1.7435 was recorded 0.7 in excess of the RMSE indicated by the case 1 model. This is an indication that the residuals are closer to the fitted line in the case 2 model, and it is evident from the fitted regression plot shown in Figure 4.15. The case 2 model posited regression R, of 1 in the training and testing phase of 0.00001 more than the case 1 model, which indicated R of 0.9999 in the training and testing phase respectively. This further establishes the case 2 model as the best performed model. Alhaji (2016) recorded R of 1 in a statistical model for predicting elastic modulus of concrete. Based on the error and regression values, the case 2 model is selected as the best model for predicting the modulus of elasticity of concrete using Bida natural gravel as coarse aggregates. The weights and bias of the ANN for the selected case 2 model with the least MSE, RMSE and highest R in the training, validation and testing phase are presented in Appendix I. Accordingly, the model equation for the selected case 2 model is given in Equation 4.5 as:

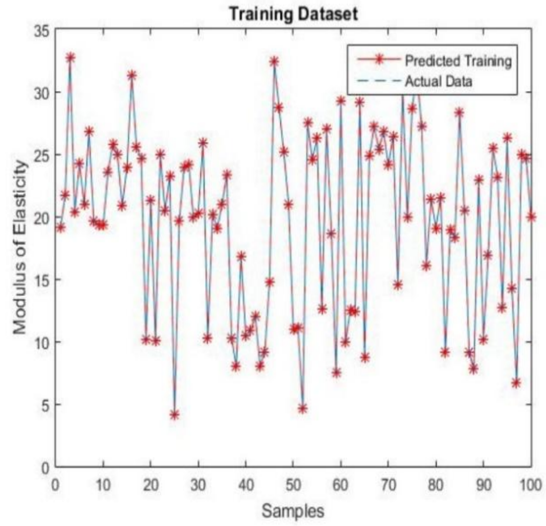
$$\boldsymbol{\psi}_{\text{output}} = \mu\left(\sum_{i=1}^{n} wij \, . \nabla - 0.0450\right) \quad (4.5)$$

Table 4.14: Performance result for cases 1 and 2 models (modulus of elasticity)

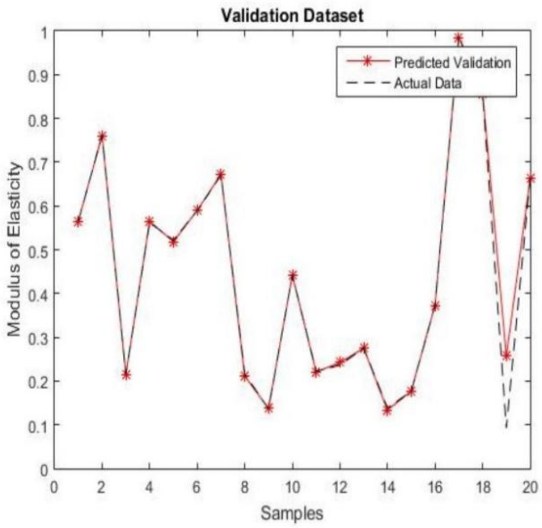
Performance	MSE	RMSE	R	Hidden layer function/Architecture
Training	0.0060	0.0776	0.9999	Tansig/5-75-1
	$3.9616xe^{-07}$	$6.2941xe^{-04}$	1.0000	Logsig/5-67-1
Validation	1.1110	1.0540	0.9906	Tansig/5-75-1
	3.0398	1.7435	0.9735	Logsig/5-67-1
Testing	0.0051	0.0714	0.9999	Tansig/5-75-1
	$3.9310xe^{-07}$	$6.2698xe^{-04}$	1.0000	Logsig/5-67-1



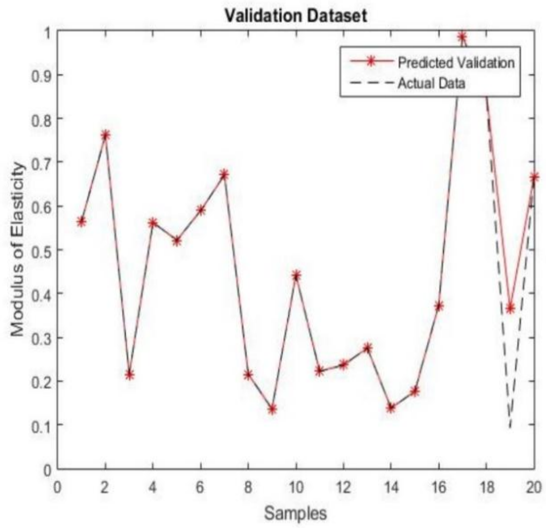
(a) Performance for Training Phase (Tansig)



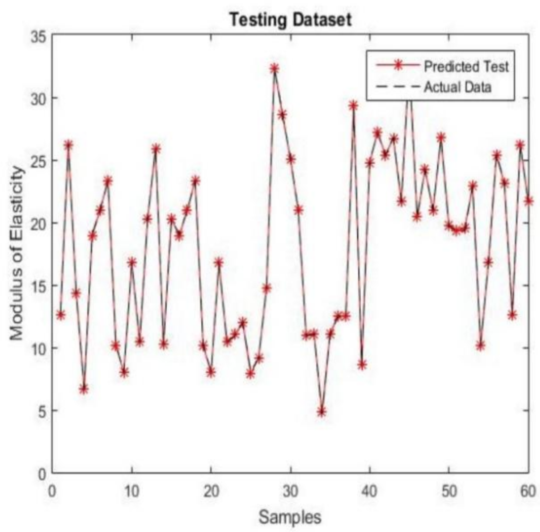
(b) Performance for Training Phase (Logsig)



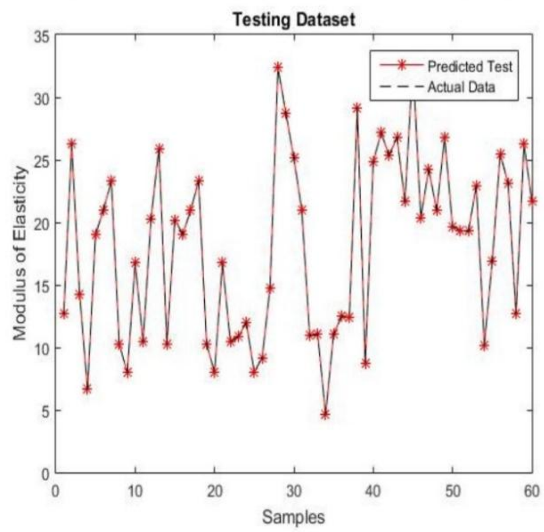
(c) Performance for Validation Phase (Tansig)



(d) Performance for Validation Phase (Logsig)

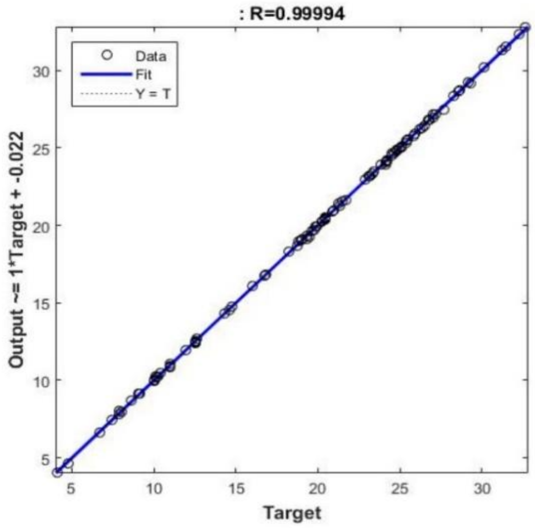


(e) Performance for Testing Phase (Tansig)

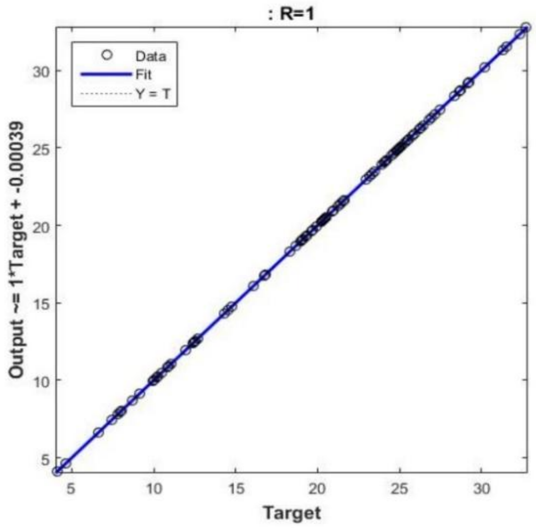


(f) Performance for Testing Phase (Logsig)

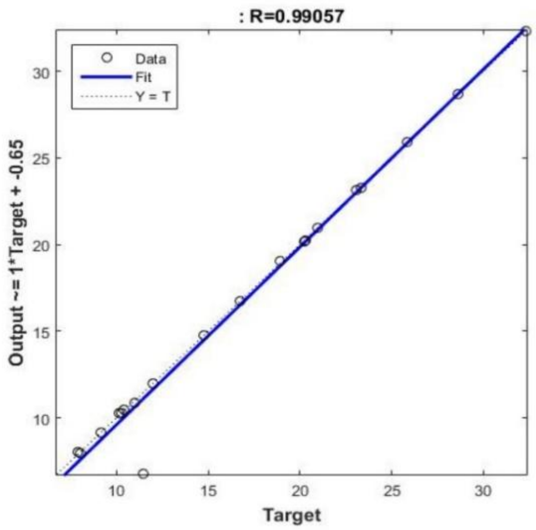
Figure 4.14: Relationship of actual to predicted results for cases 1 and 2 (modulus of elasticity model).



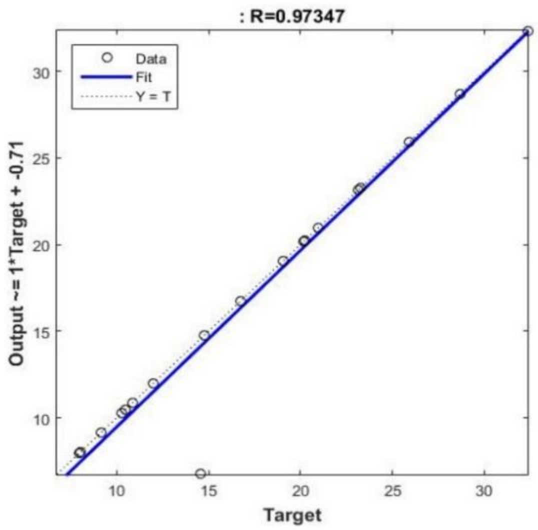
(a) Regression for Training Phase (Tansig)



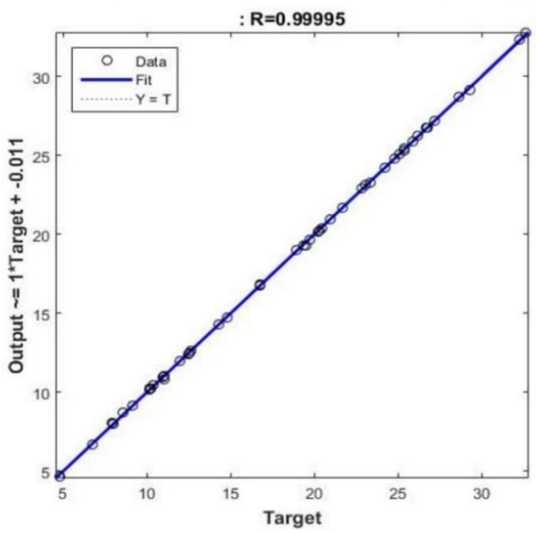
(b) Regression for Training Phase (Logsig)



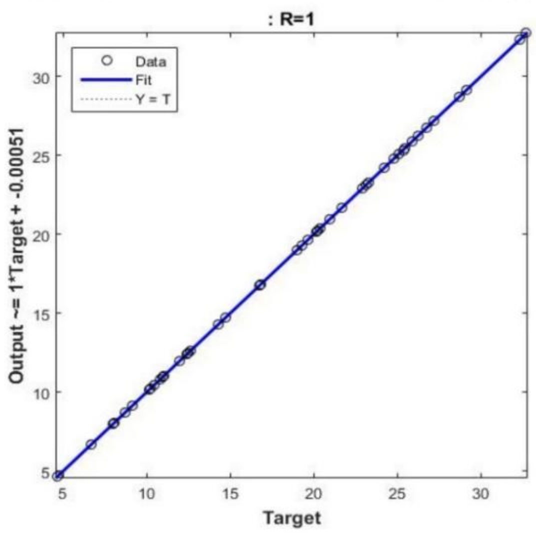
(c) Regression for Validation Phase (Tansig)



(d) Regression for Validation Phase (Logsig)



(e) Regression for Testing Phase (Tansig)



(f) Regression for Testing Phase (Logsig)

Figure 4.15: Regression result for cases 1 and 2 modulus of elasticity model.

CHAPTER FIVE

5.0 CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

Based on the finding from the research, the following conclusions were made;

The fine aggregate recorded specific gravity of 2.60, moisture content of 2.23, water absorption of 1.89 and uncompacted and compacted bulk densities of 1735.22 and 1634.06 kg/m^3 respectively. Thus, these results and the coefficient of curvature (Cc) of 3 and coefficient of uniformity (Cu) of 1.23 obtained from sieve analysis, the fine aggregate was found to be well – graded, while containing majorly coarse particles. The sand was, therefore, suitable for concrete production. The Bida Natural Gravel (BNG) showed an aggregate impact value of 24.10 and aggregate crushing value of 27.27. It also recorded specific gravity of 2.62, moisture content of 0.5, water absorption of 1.93 and with uncompacted and compacted bulk densities of 1939.28 and 1728.70 kg/m^3 respectively. In addition, it recorded Cc of 1.24 and Cu of 1.63. Based on the observed properties, it was concluded that the BNG is suitable for concrete production and possess sufficient strength to withstand shock. This corroborates other earlier works that have been executed in this wise.

The slump recorded were categorised as no slump, low slump, medium slump and very high slump of concrete based on BS EN 206 – 1 (2006). The highest slump of 270 mm was recorded when using w/c of 0.60, ca/ta of 0.55 and ta/c of 3.00, while no slump was recorded while using w/c of 0.40, ca/ta of 0.65, 0.60 and 0.55 and ta/c ratio of 6.

The highest compressive strength, flexural strength and splitting tensile strength of 44.30, 7.60 and 3.42 N/mm^2, as well as, modulus of elasticity of 32.74 kN/mm^2 was recorded using low w/c ratio of 0.40, medium ca/ta ratio of 0.55 and low ta/c ratio of 3.00 while the lowest compressive strength, flexural strength and splitting tensile strength of 7.79, 1.60 and 0.57 N/mm^2 respectively and elastic modulus of 4.09 kN/mm^2 were recorded while using low w/c ratio of 0.40, medium ca/ta ratio of 0.60 and high ta/c ratio of 6.00.

Five different Artificial Neural Network (ANN) models were developed for slump, compressive strength, flexural strength, splitting tensile strength, as well as, modulus of elasticity. Based on error indices and goodness of fit, a 5-89-1 ANN architecture with a tangent sigmoid activation function was found to be sufficient in predicting slump data for concrete using Bida Natural Gravel (BNG) as aggregates. A 5-69-1 ANN architecture with tangent sigmoid activation function was found to be sufficient in predicting compressive strength data while a 5-91-1 ANN architecture with logistic sigmoid activation function was found to perform best in predicting flexural strength of concrete using BNG as coarse aggregate. Architecture with 5 input neurons, 91 hidden neurons and 1 output neuron (5-91-1) was adjudged to best predict the splitting tensile strength of concrete containing BNG using tangent sigmoid activation function, while a 5-67-1 ANN architecture with a logistic sigmoid activation function was selected for predicting the elastic modulus of concrete containing BNG.

5.2 Recommendations

From the results obtained in this research, the following recommendations are made;

i. Bida Natural Gravel (BNG) is recommended for use in the production of normal weight concrete based on the numerical and experimental results of the physical and mechanical properties.

ii. Using a maximum BNG size of 20 mm and a w/c ratio of 0.40, 0.50 and 0.60, ca/ta ratio of 0.55, 0.60 and 0.65, as well as, a ta/c ratio of 3.00, 4.50 and 6.00, is recommended for the production of concrete in the normal strength class.

iii. The developed artificial neural network models for slump, compressive strength, flexural strength, splitting tensile strength and modulus of elasticity are recommended to be used for predicting properties and performance of concrete using BNG as coarse aggregate.

5.3 Contribution to Knowledge

i. Comprehensive information on physical and mechanical properties of BNG is available for reference.

ii. Data on the fresh and hardened properties of concrete produced using BNG is documented for future reference.

iii. ANN models for predicting the slump, strength and modulus of elasticity of concrete produced using BNG is documented.

5.4 Area for Further Study

i. Advanced studies on the prediction of the durability properties of concrete containing BNG should be caried out.

ii. BNG should be used in the production of other types of concrete such as high performance, high strength and pervious concrete.

iii. Properties of concrete made using BNG should be modeled using other artificial intelligence techniques such as fussy logic and genetic algorithm.

REFERENCES

Abbasi, A. F., Ahmad, M. & Wasim, M. (1987). Optimization of concrete mix proportioning using reduced factorial experimental technique, *ACI Materials Journal*, 84(1), 55-63.

Abdullahi, M. (2006). Properties of some natural fine aggregates in Minna, Nigeria and environs. *Leonardo Journal of Sciences*, 8(1), 1-6

Abdullahi M. (2009). Development of an Expert System for lightweight concrete mix design. *Unpublished PhD Thesis submitted to College of Graduate Studies, Universiti Tenaga Nasional,* Malaysia.

Abdullahi M. (2012). Effect of Aggregate type on the compressive strength of concrete, *International Journal of Civil and Structural Engineering*, 2(3), 791-800.

Abebe, D. (2005). The Need for Standardization of Aggregates for Concrete Production in Ethiopian Construction Industry. *Unpublished Research submitted to Civil Engineering Department, Addis Ababa University*, Ethiopia.

ACI 211(2001). *Standard Practice for Selecting Proportions for Normal, Heavyweight, and Mass Concrete*. American Concrete Institute, Farmington Hills, Michigan

ACI 221R (1996). *Guide for Use of Normal Weight Aggregates in Concrete*. American Concrete Institute, Farmington Hills, Michigan

ACI 318 R-05 (2005). *Building Code Requirements for Structural Concrete*. Farmington Hills, Michigan

ACI 363 (2010). *Report on High-Strength Concrete*. American Concrete Institute, Farmington Hills, Michigan

Aginam, C. H., Chidolue, C. A., & Nwakire, C. (2013). Investigating the effects of coarse aggregate types on the compressive strength of concrete. *International Journal of Engineering Research and Applications (IJERA),* 3(4), 1140-1144.

Ahmet, O., Murat, P., Erdogan, O., Erdogan, K., Naci, C. & Asghar, B. (2006). Predicting the compressive strength and slump of high strength concrete using neural network. *Construction and Building Materials*, 20, 769-775.

Aitcin, P. C. (1998). *High Performance Concrete.* E&FN SPON Publisher, London and New York

Akande, S. O., Ojo, O. J., Erdtmann, B. D. & Hetenyi M. (2005). Paleoenvironments, organic petrology and rock-eval studies on source rock facies of the lower maastrichtian patti formation, Southern Bida Basin. *Nigeria Journal of African Earth Science,* 41(2), 394-406.

Akkurt, S., Tayfur, G. & Can, S. (2004). Fuzzy logic model for the prediction of cement compressive strength. *Cement and Concrete Research*, 34(8), 1429-1433.

Alshihri, M. M., Azmy, A. M. & El-Bisy, M. S. (2009). Neural networks for predicting compressive strength of structural light weight concrete. *Construction and Building Materials*, 23(6), 2214-2219.

Alexander, M. &Mindess, S. (2005). *Aggregates in Concrete*. Taylor & Francis, New York.

Alhaji, B. (2016). *Statistical Modelling of Mechanical Properties of Concrete Made from Natural Coarse Aggregates from Bida Environs.* Unpublished PhD Thesis Submitted to Department of Civil Engineering, Federal University of Technology, Minna.

Apebo, N. S., Iorwua, M. B. & Agunwamba, J. C. (2013). Comparative analysis of the compressive strength of concrete with gravel and crushed over burnt bricks as coarse aggregates, *Nigerian Journal of Technology*, 32(1), 7-12.

ASTM C42 - 90 (1992). *Standard Test Method for Obtaining and Testing Drilled Cores and Sawed Beams of Concrete*. ASTM International, West Conshohocken, Pennsylvania

ASTM C78 (2021). *Standard Test Method for Flexural Strength of Concrete (Using Simple Beam with Third-Point Loading).* ASTM International, West Conshohocken, Pennsylvania

ASTM C94 (2021). *Standard Specification for Ready-Mixed Concrete*. ASTM International, West Conshohocken, Pennsylvania

ASTM C150-97 (2000). *Standard Specification for Portland Cement*. ASTM International, West Conshohocken, Pennsylvania

ASTM C496-71 (2004). *Standard Test Method for Splitting Tensile Strength of Cylindrical Concrete Specimens*. ASTM International, West Conshohocken, Pennsylvania

Bamigboye, G.O., Adedeji, A. A., Olukanni, D. O., & Jolayemi, J. K. (2017). Effect of granite/gravel (washed) combination on fresh properties of self-compaction concrete. *International Journal of Applied Engineering Research*, 12(15), 10-18.

Bandara, T.M.D.K. (2013). Simulation of regression analysis by an automated system utilizing artificial neural networks. *International Journal of Latest Trends in Computing*, 2(3), 378 -391

Baykasoglu, A., Dereli, T. & Tanis, S. (2004). Prediction of cement strength using soft computing techniques. *Cement and Concrete Research*, 34(11), 2083-2090.

Bisgaard, S. (1997). Accommodating four-level factors in two-level factorial. *Quality Engineering,* 10(1), 205-206.

Bilgehan, M. & Turgut, P. (2010). The use of neural networks in concrete compressive strength estimation, *Computers and Concrete*, 7(3), 271-283.

Boukhatem, B., Kenai, S., Hamou, A. T., Ziou, D. J. & Ghrici, M. (2012). Predicting concrete properties using neural networks (nn) with Principal Component Analysis (PCA) technique. *Computer and Structures,* 10(6), 1-17.

Box, G.E.P. & Behnken, D.W. (1960). Some new three level designs for the study of quantitative variables. T*echnometrics*, 2(1), 455-475.

Box G.E.P., Hunter W.G., & Hunter J. S. (1978). *Statistics for Experimenters. An Introduction to Design, Data Analysis, and Model Building.* John Wiley & Sons, New York.

Box, G.E.P. & Draper, N.R. (1987). *Empirical Model-Building and Response Surfaces*. John Wiley & Sons, New York

BS 8110 (1997). *Structural Use of Concrete-Part 1: Code of Practice for Design and Construction*. British Standards Institution, London.

BS 812 - 1 (1975). *Methods for Sampling and Testing of Mineral Aggregates, Sands and Fillers - Sampling, Size, Shape and Classification*. British Standards Institution, London

BS 812 - 112 (1990). *Testing Aggregates. Method for Determination of Aggregate Impact Value*. British Standards Institution, London

BS 5328 - 2 (2002). *Concrete Methods for Specifying Concrete Mixes*. British Standards Institution, London.

BS 8500 - 2 (2015). *Concrete - Specification for Constituent Materials and Concrete*. British Standards Institution, London.

BS 812 - 2 (1995). *Testing Aggregates-Methods for determination of density*. British Standards Institute, London

BS 882 (1992). *Specification for Aggregates from Natural Sources for Concrete*. British Standards Institution, London.

BS 1881 - 102 (1983). *Methods of Testing Concrete-Method for Determination of Slump*. British Standards Institution, London

BS 812 - 110 (1990). *Testing Aggregates. Method for Determination of Aggregate Crushing Value.* British Standards Institution, London

BS 1881 - 117 (1983). *Method for Determination of Splitting Tensile Strength.* British Standards Institution, London

BS 1881 - 118 (1983). *Testing concrete-Method for Determination of Flexural Strength*. British Standards Institution, London

BS 1881 - 177 (1983). *Method for Determination of Tensile Splitting Strength*. British Standards Institution, London

BS 3148 (1980). *Methods of Test for Water for Making Concrete (Including notes on the Suitability of the Water).* British Standard Institution, London

BS EN 197 - 1 (2011). *Cement: Composition Specifications and Conformity Criteria for Common Cement*. British Standards Institution, London

BS EN 206 - 1 (2006). *Concrete: Specification, Performance, Production and Conformity*. British Standard Institution, London

BS EN 197- 1 (2000). *Cement- Composition, Specifications and Conformity Criteria for Common Cements*. British Standard Institution, London

BS EN 933 - 4 (2008). *Test for Geometrical Properties of Aggregates - Determination of Particle Size Distribution (Sieving Method).* British Standard Institution, London

BS EN 1008 (2002). *Mixing Water for Concrete. Specification, for Sampling, Testing and Assessing the Suitability of Water, including Water Recovered from Processes in Concrete Industry as Mixing Water for Concrete*. British Standards Institution, London.

BS EN 12620 (2008). *Aggregates for Concrete.* British Standards Institution, London.

BS EN 12350 - 6 (2009). *Testing of Fresh Concrete Density*. British Standard Institution, London

BS EN 12390 - 3 (2009). *Testing of Hardened Concrete - Compressive Strength Test Specimens*. British Standard Institution, London

BS EN 12390 - 5 (2009). *Method for Testing the Flexural Strength of Specimens of Hardened Concrete*. British Standards Institution, London.

BS EN 12390 - 6 (2009). *Testing of hardened concrete -Tensile Splitting Strength, Specification for Testing Machines*. British Standard Institution, London

BS EN 12390 - 13 (2009). *Testing Hardened Concrete-Determination of Secant Modulus of Elasticity*. British Standards Institution, London.

Cachim, P. B. (2017). *Concrete Produced using Crushed Bricks as Aggregate*. Labest and Decivil, University of Aveiro, Portugal.

Caldarone M. A. (2009). *High Strength Concrete: A Practical Guide.* Taylor and Francis Publication, London.

Caudill, M. & Butler, C. (1990). *Naturally Intelligent Systems.* MIT Press, Cambridge, MA

Cordon, W. A. & Gillespie, H. A. (1963). Variables in concrete aggregates and portland cement paste which influence the strength of concrete, *ACI Journal Proceedings,* 60(8), 1029-1052.

Cornell, J. A. (1990). *Experiments with Mixtures: Designs, Models, and the Analysis of Mixture Data*. John Wiley and Sons, New York.

Craig, R F. (2004). *Craig's Soil Mechanics*. Spon Press, London

Crow, J. M. (2008). *The Concrete Conundrum*. Chemistry World, 5, 62-66.

Diab, A. M., Elyamany, H. E., Abd-Elmoaty, A. E. M. & Shalan, A. H. (2014). Prediction of concrete compressive strength due to long term sulfate attack using neural network. *Alexandria Engineering Journal*, 53(3), 627–642.

Doug, W. (2015). *Introduction to Design and Analysis of Experiments*. Department of Mathematical & Statistical Sciences, Faculty of Science, University of Alberta.

El-Khoja, A. M. N., Ashour, A. F., Abdalhmid, J., Dai, X. & Khan, A. (2018). Prediction of rubberised concrete strength by using artificial neural networks. *International Journal of Structural and Construction Engineering,* 12(11), 117-125.

Ezeldin, A. S. & Aitcin, P. C. (1991). Effect of coarse aggregate on the behavior of normal and high-strength concretes. *Cement, Concrete, and Aggregates,*13(2), 121-124.

Ezeokonkwo, J. U., Okolie, K. C. & Ogunoh, P. (2015). Assessment of qualities of coarse aggregate used in concrete production in Anambra State, Nigeria. J*ournal of Scientific and Engineering Research,* 2(2), 40-51.

Fakuyi, F. F., Aliu, A.O., Olabisi, W. K., & Akindureni, Y. (2019). Strength positives between gravel and palm kernel shell in concrete formation. *The International Journal of Engineering and Science (IJES),* 8(9), 42 - 45.

Flood, I. & Kartam, N. (1994a). Neural network in civil engineering I: principles and understandings. *Journal of Computing in Civil Engineering. - ASCE,* 8(2), 131-148.

Flood, I. & Kartam, N. (1994b). Neural network in civil engineering II: Systems and applications, *Journal of Computing in Civil Engineering. - ASCE*, 8(2), 149-162

Fowler, D.N. & Quiroga, A. (2003). The effect of aggregates characteristic on the performance of Portland cement concrete, *International Center for Aggregates Research ICAR*, 1(1), 382-400

Gambhir, M. L. (2001). *Concrete Technology: Theory and Practice*. 5th Edition McGraw Hill Publisher, India

Gupta, S. (2013). Using artificial neural network to predict the compressive strength of concrete containing nano-silica. *Civil Engineering and Architecture,* 1(3), 96-102, http://www.hrpub.org DOI: 10.13189/cea.2013.010306

Habeeb, G. M. (2000). *Residual Mechanical Properties of High Strength Concrete Subjected to Elevated Temperature*, PhD. Thesis College of Engineering, Department of Civil Engineering, Al–Mustansiria University Baghdad, Iraq

Hajela, P. & Berke, L. (1991). Neurobiological computational models in structural analysis and design. *Computer Structure,* 41(4), 657-667

Hebb, D.O. (1949). *The Organization of Behavior*. Wiley, New York

Hodgkin, A. L. & Huxley, A. F. (1952). A quantitative description of membrane current and its application to conduction and excitation in nerve, *Journal of Physiology,* 117(2), 500-544

Hola, J. & Schabowicz, K., (2005). Application of artificial neural networks to determine concrete compressive strength based on non-destructive tests, *Journal of civil Engineering and Management*, 10(1), 23-32

Husem, M. (2006). The effect of high temperature on compressive and flexural strengths of ordinary and high-performance concrete. *Fire Safety Journal,* 41, 155- 163

Ikechukwu, E. & Chidozie, C., (2015). Modelling compressive strength of concretes incorporating termite mound soil using multi-layer perceptron networks: A case study of Eastern Nigeria. *International Journal of Recent Research and Applied Studies,* 24(01), 19-30

Ilyasu, S.M. (2014). *Performance of Bida Natural Deposit Stone as Coarse Aggregate in Self-Compacting Concrete*. Unpublished M.Eng Thesis Submitted to Department of Civil Engineering, Federal University of Technology, Minna

Jackson N. (1980). *Civil Engineering Materials*, Second Edition. Paperback, Palgrave, London

Jackson N., & Dhir R. K., (1996). *Civil Engineering Materials*, Fifth Edition, Paperback, Palgrave, London

Jin, Y.Y, Hyunjun, K., Young-Joo, L. & Sung-Han, S. (2019). Prediction model for mechanical properties of lightweight aggregate concrete using artificial neural network, *Materials*, 12(1), 26-78

Joseph. O. U. & Maurice. E. E. (2012). Flexural and tensile strength properties of Concrete using lateritic sand and quarry dust as fine aggregate. *ARPN Journal of Engineering and Applied Sciences*, 7(3), 3-24

Kamran, M. (2015). *Concrete Technology - Aggregates for Concrete*. Winter Quarter, University of Washington, USA

Kanawade, B.D., Kulkarni, V. P., Kandekar, S. B., & Mehetre, A. J. (2014). Compression and split tensile strength of concrete containing different aggregates. *International Journal of Engineering Research & Technology (IJERT)*, 3(3), 469 – 473.

Kaplan, M. F. (1959). Flexural and compressive strength of concrete as affected by the properties of coarse aggregate, *ACI Journal Proceedings,* 30(11), 1193-1208.

Kartam, N., Flood, I. & Garrett, J.H. (1997). *Artificial Neural Networks for Civil Engineers: Fundamentals and Applications*, ASCE, New York.

Kett, I. (2000). *Engineered Concrete: Mix Design and Test Methods (Concrete technology series)*, CRC Press LLC, Taylor and Francis, USA

Kirtikanta, S., Sarkar, P., & Robin, D. P. (2016). Artificial neural networks for prediction of compressive strength of recycled aggregate concrete. *International Journal of Research in Chemical, Metallurgical and Civil Engineering,* 3(1), 2349-1450.

Khuri, A.I. & Cornell, J.A. (1987). *Response Surfaces:* Designs and Analyses. Marcel Dekker, Inc.

Kim, J. I., Kim, D. K., Feng, M. Q., & Yazdani, F., (2004). Application of neural networks for estimation of concrete strength. *Journal of Materials in Civil Engineering*, 16(3), 57-264.

Kucche, K. J., Jamkar, S. S. & Sadgir, P. A. (2015). Quality of water for making concrete - A review of literature. *International Journal of Scientific and Research Publications*, 5 (1), 1–10.

Lee, S. C., (2003). Prediction of concrete strength using artificial neural networks. *Engineering Structures*, 25, 849-857.

Mack, W.N. & Leistikow, E.A. (1996). *Sands of the World*. Scientific American.

Maneeth, P. D & Chandrashekar, A. (2014). Performance appraisal of river stone as a coarse aggregate in concrete. *International Journal of Engineering Research and Applications*, 4(1), 93-102

Mansour, M.Y., Dicleli, M., Lee. J.Y. & Zhang, J. (2004). Predicting the shear strength of reinforced concrete beams using artificial neural network, *Engineering Structures*, 26 (6), 781-799.

Marijana, H., Emmanuel, K.N, Naida, A., Ivana, M. & Tanja, K.S, (2019). Modelling the influence of waste rubber on compressive strength of concrete by artificial neural networks, *Materials*, 12(1), 561 – 579

MATLAB (2015). *Statistics Toolbox*. MathWorks, Inc., Natick, Massachusetts, United States.

McCulloch, W.S. & Pitts, W. (1943). A logical calculus of the ideas immanent in nervous activity. *Bulletin of Mathematical Biophysics*, 5(1), 115 - 202

Mehta, P.K. & Monteiro, P.J.M. (1993). *Concrete,* McGraw-Hill, Pennsylvania, New York

Mehta P.K. & Monteiro P.J.M (2001). *Concrete: Microstructure, Properties and Materials.* McGraw-Hill, Pennsylvania, New York

Meyers, R.H & Montgomery, D.C. (1995*). Response Surface Methodology: Process and Product Optimization using Designed Experiments*. John Wiley & Sons, USA

Minitab 17 Statistical Software (2017). *Computer Software*. State College, PA: Minitab, Inc. (www.minitab.com)

Mohammed, I. J., Mazni A., Mohammed, K.A.M, Koh, H.B, Norzila, O., Aeslina, A. K, Muhammad, A.R & Faisal, S.K. (2013). relationship between compressive, splitting tensile and flexural strength of concrete containing granulated waste polyethylene terephthalate (PET) bottles as fine aggregate, *Advanced Materials Research*, 795, 356-359.

Montgomery, D.C. & Voth, S.R. (1994). Multicollinearity and leverage in mixture experiments, *Journal of Quality Technology* 26(1), 96-108.

Montgomery, D. C. (1997). *Design and Analysis of Experiments*. Fourth Edition. John Wiley, New York

Montgomery, D.C. (2001). *Design and Analysis of Experiments,* Fifth Edition. John Wiley & Sons, New Jersey, USA

Nawy, E. G. (2008). *Concrete Construction Engineering Handbook*, Second Edition, CRC Press, Taylor & Francis Group, Florida, USA

Neela, D., Shreenivas L., & Sushma K. (2014). Modeling compressive strength of recycled aggregate concrete by artificial neural network, model tree and non-linear regression, *International Journal of Sustainable Built Environment*, 3, 187–198

Neville A.M. & Aitcin P.C. (1998). High performance concrete: An overview. *Materials and Structures*, 31(1), 111-117.

Neville, A.M. & Brooks, J.J (2001). *Concrete Technology*, Pearson Longman, New York, USA.

Neville, A.M. (2011). *Properties of Concrete.* Pearson Longman, New York, USA.

Newman, J. & Choo, B.S. (2003). *Advanced Concrete Technology-Constituent Materials*. Elsevier.

Ni, H.-G. & Wang, J.-Z. (2000). Prediction of compressive strength of concrete by neural networks. *Cement and Concrete Research*, 30(8), 1245-1250.

NIS 87 - Nigerian Industrial Standard (2004). *Standard for Sandcrete Blocks*. Standard Organization of Nigeria, Lagos, Nigeria.

Nishant, R., Abhishek, T. & Alok, K.S. (2016). High performance concrete and its applications in the field of civil engineering construction, *International Journal of Current Engineering and Technology,* 6(3), 2347-5161.

Nuhu, G.O. (2009). *Geology and Mineral Resources of Nigeria*, Springer Dordrecht Heidelberg, London

Olajumoke, A. M., & Lasisi, F. (2014). Strength evaluation of concrete made with dug-up gravel from Southwestern Nigeria. *Journal of Failure Analysis and Prevention*, 14(3), 384–394. doi:10.1007/s11668-014-9812-8

Olawuyi, B.J. (2016). *The Mechanical Behavior of High-Performance Concrete with Superabsorbent Polymers (SAP)*. PhD Dissertation presented to Stellenbosch University, South Africa.

Ode, T., & Eluozo, S. N. (2016). Compressive strength calibration of washed and unwashed locally occurring 3/8 gravel from various water cement ratio and curing age. *International Journal of Engineering Research and General Science*, 4(1), 462-483.

Omar, B.S (2009). *Investigation on the Engineering Properties of Coarse Aggregate Locally Available in Garissa County*. Final Year Research Submitted to: Department of Civil and Construction Engineering, University of Nairobi, Kenya.

Orr, D. M. F., (1972). Factorial experiments in concrete research, *ACI Journal Proceedings,* 59*(*10), 619-624.

Otunyo, A. W., & Jephter, B. G. (2018). Predictive model for compressive strength of concrete made from recycled concrete coarse aggregates. *Nigerian Journal of Technology (NIJOTECH),* 37(3), 633-639.

Osama, M.A.D. & Sagady, H.S. (2013). Production and properties of high strength concrete for heightening concrete dam in Sudan, *International Journal of GEOMATE*, 4(2), 539-545.

Oztas¸ A., Pala, M. Ozbay, E. Kanca, E. Glar, N. C. A & Bhatti, M.A. (2006). Predicting the compressive strength and slump of high strength concrete using neural network, *Construction and Building Materials,* 20(9), 769-775.

Ozturan, M., Kutlu, B. & Ozturan, T. (2008). Comparison of concrete strength prediction techniques with artificial neural network approach, *Building Research Journal,* 56, 23–36.

Pala, M., Ozbay, E., Oztas¸, A. & Yuce, M. I. (2007). Appraisal of long-term effects of fly ash and silica fume on compressive strength of concrete by neural networks. *Construction and Building Materials*, 21(2), 384-394.

Palika, C., Rajendra, K.S., & Maneek K., (2008). Artificial neural networks for the prediction of compressive strength of concrete. *International Journal of Applied Science and Engineering*, 13(3), 187-204.

Pan, G. (1996). The impact of unidentified location effects on dispersion-effects identification from unreplicated factorial designs, *Technometrics*, 41, 313-326.

Pandelea, A. E., Mihai, B., Gabriela, C. & Rareş G. T. (2015). Checking the homogeneity of concrete using artificial neural network. *Building Services*, 1(1), 1-10

Peace, G.S. (1993). *Taguchi Methods*. Addison-Wesley Publishing Company, Boston, USA

Rajamane, N. P., Peter, J. A & Ambily, P. S. (2007). Prediction of compressive strength of concrete with fly ash as sand replacement material, *Cement and Concrete Composites*, 29(3), 218-223.

Rocco C.G. & Elices, M., (2009). Effect of aggregate shape on the mechanical properties of simple concrete, *Engineering Fracture Mechanics*, 72(2), 286- 298

Rumelhart, D.E., Hinton, G.E. & Williams, R.J. (1986). *Learning Internal Representation by Error Propagation.* MIT Press, Cambridge, Massachusetts, USA.

SagarTanwani, B. A. (2016). Relationship between weight and tensile strength of concrete cylinders made by partial replacement of coarse aggregates from old concrete. *International Journal of Engineering Inventions*, 5(6), 1-9.

Sallal R. A., Ali, H. N., Husam, K.H.A. & Athraa, M. N. (2018). Expansion and strength properties of concrete containing contaminated recycled concrete aggregate. *Case Studies in Construction Materials*, 2(5), 1-14.

Salihu, A.T. (2011). *A Study of the Compressive Strength of Concrete made from Bida Natural Deposit Stone*. Unpublished M.Eng Thesis Submitted to Department of Civil Engineering, Federal University of Technology, Minna.

Saridemir, M. (2009). Prediction of compressive strength of concretes containing metakaolin and silica fume by artificial neural networks, *Advances in Engineering Software*, 40(5), 350-355.

Saridemir, M. (2010). Genetic programming approach for prediction of compressive strength of concretes containing rice husk ash. *Construction and Building Materials*, 24(10), 1911-1919.

Shah, S.P & Ahmad, S.H. (1994). *High Performance Concrete: Properties and Application*. McGraw-Hill, New York.

Shakhmenko, G. & Birsh, J. (1998). Concrete Mix Design and Optimization, *2nd International Symposium in Civil Engineering*, 1–8.

Shamsad A. (2007). Optimum concrete mixture design using locally available ingredients, *The Arabian Journal for Science and Engineering*, 32(1), 27 – 33.

Shehu I. A, Mohammed A. D, Sheshi A. & Alpha A. A. (2016). Assessment of potentials of bida bush gravel on strength properties of self compacting concrete, *International Journal of Engineering Research & Technology (IJERT)*, 5(4), 476 -479

Shetty, M.S. (2005). *Concrete Technology*. S.Chand & Company Ltd., India.

Sonebi, M., Grünewald, S., Cevik, A., & Walraven, J. (2016). Modelling fresh properties of self-compacting concrete using neural network technique. *Computers and Concrete,* 18(4), 903-921.

Soudki, S., El-Salakawy, E. & Elkum, N. (2001). Full factorial optimization of concrete mix design for hot climates. *Journal of Materials in Civil Engineering,* 13(1), 427-433.

Stuart, J. R. & Peter, N. (2010) *Artificial Intelligence: A Modern Approach*, Prentice Hall, Englewood Cliffs, New Jersey

Sulymon, N., Olatokunbo, O., Olowofoyeku, A., Simon, O., Ayobami, B., Gideon, B. & Joshua J., (2017). Engineering properties of concrete made from gravels obtained in Southwestern Nigeria. *Cogent Engineering*, 4(1), 1-11

Taguchi, G. (1987). *System of Experimental Design*. International Publications, White Plains, New York.

Tijana, R., Irena, K., Marko, J., Biljana, J. & Darko, I. (2014). Comparison of Full Factorial Design, Central Composite Design, and Box-Behnken Design in Chromatographic Method Development for the Determination of Fluconazole and Its Impurities, *Analytical Letters,* 47(8,) 1334-1347.

Worldometers (2021). *World Population Prospects:* The 2021 Revision. Retrieved from: http://www.worldometers.info/world-population/nigeria-population/

Yang, W. (2015). *The Issues and Discussions of Modern Concrete Science*. Springer-Verlag, Heidelberg, Berlin

Yeh, I. C., (2006). Analysis of strength of concrete using design of experiments and neural networks, *Journal of Materials in Civil Engineering ASCE*, 18(4), 597-604

Yusuf, A., Abdullahi, M., Sadiku, S., & Aguwa, J. I. (2020). Mechanical properties of concrete using Bida natural aggregate as coarse aggregates. *Journal of Research Information in Civil Engineering,* 17(3), 4020-4032

Zahid A.C, Umer S. & Shahid B. (2015). Compressive strength of concrete using natural aggregates (gravel) and crushed rock aggregates - A comparative case study, *international journal of civil engineering and Technology,* 6(1), 21-26

Zarandi, M. H., Turksen, I. B., Sobhani, J., & Ramezanianpour, A. A., (2008). Fuzzy polynomial neural network for approximation of the compressive strength of concrete, *Applied Computing*, 8(1), 488-498.

Zia, P., Leming, M.L, & Ahmad S.H. (1991). *High Performance Concrete: A state of the Art Report*. Report No. SHRP-C/FR-91-103. Strategic Research Programme, National Research council

Zongjin, Li (2011). Advanced Concrete Technology. John Wiley & Sons, Inc., Hoboken, New Jersey.