PREDICTION AND OPTIMIZATION OF COMPRESSIVE STRENGTH OF CONCRETE CONTAINING NANOSIZED CASSAVA PEEL ASH USING ARTIFICIAL NEURAL NETWORK

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CERTIFICATION

This is to certify that this study **"Prediction and Optimization of Compressive Strength of Concrete containing Nanosized Cassava Peel Ash Using Artificial Neural Network"** was carried out by **Nwa-David, Chidobere David** with registration number: **20194190088** in partial fulfillment for the award of the degree of Master of Engineering (M. Eng) in Civil Engineering (Structural Engineering) of the Federal University of Technology, Owerri.

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DEDICATION

This research work is dedicated to the Almighty God who by his infinite mercy made this a reality.

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ABSTRACT

In this work, artificial neural network (ANN) was adopted for optimization of the compressive strength of concrete containing nano-sized cassava peel ash (NCPA) as partial replacement of cement. Levernberg-Marquardt back propagation and sigmoid function were employed in the model formulation. A total of four hundred (400) data set were presented to the network. Two hundred and forty (240) were used for training, sixty (60) were used for validation, and another sixty (60) were used for testing the network's performance. After training the network, the output and targets have an R - value of 0.99909 which is equivalent to 1. This indicates that the data used for training the network, have a good fit. Data used for this formulation were obtained experimentally. From the laboratory study, maximum compressive strength of 18.70 N/mm^2, 22.10 N/mm^2, 24.20 N/mm^2, 30.10 N/mm^2, 33.30 N/mm^2 and 36.90 N/mm^2 was achieved at a water-cement ratio of 0.75 at 19.5% replacement for 7, 14, 28, 56, 90 and 150 days curing age respectively while the corresponding ANN modelled maximum strength were 17.92 N/mm^2, 22.24 N/mm^2, 24.34 N/mm^2, 30.50 N/mm^2,33.23 N/mm^2 and 36.85 N/mm^2. The predicted values were very much close to the experimental results. However, it was deduced that the replacement of cement with NCPA must not exceed 20%, if NCPA-concrete is to be used as a structural material. Evaluating the adequacy of the network with student's T-test at 95% confidence level, proved that the model is worthy of adoption for reliable, time-effective and accurate strength-optimization of nanosized concrete.

Keywords: Nanosized Cassava Peel Ash, Mix proportion, Compressive strength, Artificial Neural Network, Concrete Optimization.

CHAPTER ONE

INTRODUCTION

1.1 Background of Study

Concrete is a fashioned composite-material that contains cement, water, fine and coarse aggregates in predetermined-mix-proportions (Bourchy, Barnes, Bessette, Chalencon, Joron, and Torrenti, 2019), with chemical or mineral admixtures that enhances its properties. Concrete utilization in the construction industry is growing rapidly and has led to stretched exigency and expending of concrete ingredients (Onwuka and Awodiji, 2013).

Nanosized concrete is produced by adding nanosized materials or particles into concrete using the right mix proportions in a suitable approach. This approach can either be size reduction or generation of materials from molecular or atomic components (Sanchez and Sobolev, 2010). ANN is applied to anticipate the strength of concrete whose cement proportion is partly replaced with nano-sized cassava peel ash.

Cement is one of the raw-materials in concrete-mix that serves as a binder between the aggregates. The need for concrete in accelerated infrastructural advancement, has placed more demand on cement production. The environmental effect of cement production is a call for concern. According to Baikerikar (2014), over 0.85 ton of carbon dioxide (CO_2), is unleashed in the environment manufacturing of 1 ton of cement. The CO_2 is one of greenhouse-gas that sponsors atmospheric warming. The ejection of this gas has led to the depletion of the ozonosphere with consistent effects including earthquakes, flooding, hurricanes and arrival of new viruses (Andrew, 2018).

In addition to the emission of CO_2, limestone deposits are expended in the process of cement production. The high energy consumption from cement production has made the cement industry to be monopolized by a handful investors, who can afford the expensive production cost of cement. The expensive price of the product, makes it challenging for average or low-income earners to construct their own houses. On that account, there is pressure to develop alternative binding materials.

The worth of concrete is largely influenced by its strength attribute. In the service life of concrete, strength is a crucial variable. Conventionally, laboratory trial mixes, are employed to evaluate concrete strength and this is costly. One of the major reasons why most buildings collapse in Nigeria, is weak concrete mixes (Olujumoke, Oke, Fajobi, and Ogedengbe, 2009) and this has catastrophic environmental socio-economic aftermath (Arum, 2008). Efforts are made by researchers to develop and employ techniques that can be used for prediction of optimal strength in order to circumvent the challenges of experimental determination.

Over the years, engineers and architects have considered conventional concrete to be unattractive due to some limitations such as cracks and creep development, susceptibility to efflorescence, expansion and shrinkage. Although, admixtures had been used to modify the concrete properties, the shortcomings are still many. The need for infrastructural development have drawn the attention of researchers on improvement of the properties of concrete. And this has led to concrete nanotechnology-adding nanosized materials to concrete.

1.2 Statement of Problem

Globally, the cement industry generates about 1.7 billion tons of carbon dioxide (CO_2) and over 8% of man-made CO_2 ejection (Afsah, 2004). According to Craig (2017), CO_2 global emission escalated to 40 billion metric tons from the industries and fossil fuels. This is dreadful, and suitable techniques to save the globe from devastation coming from human activities is needful.

The use of traditional concrete has led to durability problem resulting to early replacement or high maintenance costs. Intense research has been geared towards the improvement of these conventional concrete. Nanotechnology in concrete making is an emerging area of research interest.

The pivotal role of the construction industry in the economy of any nation is indubitable. Cases of structural collapse are common in Nigeria today. This collapse has often been linked to low concrete strength. Laboratory investigation for the strength properties of concrete applied in infrastructures, is quiet costly (Nwobi-Okoyea, Umeonyiagub, Nwankwo, 2013). For a very long time, prediction of concrete-strength has been a notable matter in the area of concrete technology (Mahajan and Bhagat, 2022). This study attempts to formulate ANN model for optimizing concrete's compressive strength.

1.3 Objectives of Study

The main objective of this study is the prediction and optimization of compressive strength of nanosized cassava peel ash-cement concrete using artificial neural network method. The specific objectives are to:

i. Determine the properties of fresh nanosized cassava peel ash (NCPA) concrete.
ii. Determine the compressive strengths of NCPA-concrete at varying curing ages.
iii. Develop a model with artificial neural network (ANN) for predicting the compressive strength of NCPA-concrete.
iv. Evaluate the performance of the model using percentage error method and student's T-test.

1.4 Justification of Study

The request on cement for concrete production will shrink as well as its global warming effect, if nanosized-cassava-peel-ash (NCPA) is applied continuously in concrete mixes. Cassava peel will no longer be considered as waste product as its usefulness becomes indisputable; hence massive cultivation of cassava for numerous utilizations will be encouraged.

Nanosized materials in concrete, minimizes the percentage of cement-content required in it hence it will reduce cost. Concrete properties are improved by incorporating nano particles. Nanoparticles enhance the hydration process and even fill the micro voids (Ramakrishma and Sundararajan, 2019). Basically, nanosizing materials for concrete production improves compressive and flexural strength of concrete at early age as result of its high surface to volume ratio (Rao, Rajasekharb, Vijayalakshmic, Vamshykrishnad, 2015). Hence, using nanosized cassava peel ash, will produce eco-friendly concrete.

Statistical and computational models can be adopted to obtain the most suitable proportioning of concrete constituents (Akeke, Nnaji and Udokpoh, 2021). ANN has attracted more research interest as a result of its effectiveness and simplicity in computational model development (Nyarko, Nyarko, Ademović, Miličević, and Šipoš, 2019). Low-concrete-strength is a major reason for most structural failure (Ojeda, Bocanegra, Huatangari, 2021), and this strength can be predicted using artificial neural network. The quality of concrete applied in different engineering works can be controlled through the use of ANN as its strength prediction is relevant and reliable.

1.5 Scope of Study

Desired durability performance of concrete and a self-sufficient means of shelter, are achieved through the incorporation of supplementary cementitious materials (SCMs). Among many SCMs, this study considered only cassava peel ash in its nanosized form.

The only engineering hardened property of concrete evaluated in this work is the compressive strength. Reliable and fast predictability of concrete compressive strength is essential in estimating the time required to open the concrete formwork, project scheduling, and quality control.

Various artificial intelligence methods can be employed to obtain the most accurate input and output relationships within concrete mixtures and to overcome the shortcomings of traditional methods, which include expensive experimental costs, time wastage and inaccurate compressive strength prediction results. However, only artificial neural networks (ANN), is adopted in this work.

The ANN prediction is validated with student's statistical test tool only. This study also outlined its contributions to knowledge, recommendation and conclusion.

CHAPTER TWO

LITERATURE REVIEW

2.1 Concrete

Concrete is globally the most relevant and commonly used structural material (Bisht and Ramana, 2018). Among other materials, it is the most common and aged, on account of its availability, durability and ability to sustain extreme-weather conditions. The rise in building projects has led to increased concrete utilization and it is reckoned to magnify in the next twenty years (Onwuka, Anyaogu, Chijioke, and Okoye, 2013).

Concrete is known for its significant compressive strength. Materials like polymers and steel are more expensive and uncommon compared with concrete materials. Contrary to other materials, concrete can be handled to serve an array of performance stipulations. By tonnage, concrete production is much more than steel (Li, 2011) and according to Mehta & Monteiro (2006), concrete is employed today greater than how it was used thirty years ago.

Khurmi and Grupts (2006) explained concrete as combination of cement, sand, stone and water which hardens when placed in forms and cured. Bhavikatti (2001), explained concrete as intimate mixture of binding materials, water, fine and coarse aggregates. Concrete is a conglomerate elements comprised of coarse and fine aggregate joined together with cement paste that solidifies with time. Cementitious materials and admixtures may be included to improve its attributes. A substantial concrete is obtained when the constituents are properly mixed and prepared.

Concrete is a structural material with numerous applications in engineering. It is widely employed in building-construction (foundations, columns, beams, slabs and roof slabs), road pavements, airport pavements, storage dams, water reservoirs, tunnels, atomic power reactors and power-generating plants.

2.2. Concrete Constituents

Each constituent of concrete in their varied mix proportions, characterize the properties of concrete (Naderpour, Rafiean, and Fakharian, 2018). The beauty of this composite is that its constituents seem to be everywhere and are readily-available almost anywhere in the world. It can be made in all sorts of conceivable shapes. Concrete is easily and readily prepared. The constituents for concrete are fractioned and tailored to produce concrete with specific strength and durability, so as to suit the job's purpose. Its constituents include cement, aggregates, water and admixtures.

2.2.1 Cement

The contribution of cement in concrete-production, is salient as it largely determines the mix properties such as durability, shrinkage, workability and compressive strength (Baykasoglu, Dereli, and Tanis, 2004). The strength-matrix is developed as the cement particles react with water and binds with aggregates during hydration. The essence of cement is to bind the concrete mixture and it comprises about 7-15 % of concrete (Fahl, 2009). Its cohesive and adhesive features enhance its bonding ability. It can also set and harden autonomously (Neville, 2006).

Based on cement's consumption using water, cements can either be hydraulic or non-hydraulic. Hydraulic cements set in wet condition, retains stability and strength during water contact and they are safe from chemical attack. Non hydraulic cements set in the absence of water with carbon dioxide in the air, but they are easily attacked after setting by most aggressive chemicals. Portland cement is more commonly used among different varieties of hydraulic cement (BS 5328: Part 2: 1997).

2.2.1.1 Types of Cement

There are mainly five types of cement. They are; ordinary portland cement, modified portland cement, high-early strength cement, low heat portland cement, and sulfate resistant portland cement (ASTM, 1990; Dunuweera and Rajapakse, 2017; Gowda and Ranganath, 2023). Other cements include; white portland cement, high alumina cement, portland pozzolana cement, portland blast-furnace slag cement, masonry cement, natural cement and expansive cement (Li, Liang and Li, 2011; Shetty, 2005).

The most commonly used is the ordinary portland cement, which is a finely-ground calcareous material containing compounds of alumina, lime, iron and silica. The paste it forms when mixed with water, hardens and binds both coarse and fine aggregates. Alumina cements are highly effective types of binders. The 28-day strength of Portland cement is equivalent to the strength of alumina cement at the age of 3 days (Krivoborodov and Samchenko, 2019). These cements are employed in the construction of objects susceptible to mineralized water, construction of waterproof structures, drilling of oil/gas wells, elimination of accidents, urgent construction of foundations for cars, restoration of destroyed structures, repairs after fires and sulfur dioxide (Klaus, Neubauer and Goetz-Neunhoeffer, 2013).

Portland Pozzolana Cement is produced by including pozzolanic materials to ordinary portland cement (Waghmare, Patil and Maske, 2021). Artificial pozzolana materials such as rice husk, blast furnace slag, fly ash, are used in making this type of cement (Pal and Gupta, 2020). This pozzolanic materials helps to enhance the strength of concrete, decreases the rate of natural resources consumption and reduces the effect of environmental pollutants. These materials are economical and reliable (Wong, Kok and Wong, 2020).

Portland blast-furnace slag cement is a mixture of Ordinary Portland Cement and 30-50% granulated blast furnace slag (Rahman, Abo-El-Enein, Aboul-Fetouh, Shehata, 2011).

Granulated-blast-furnace-slag is a waste product of the manufacture of iron. The amount of iron and slag being obtained is in the same order. This slag is primarily a mixture of lime, silica, alumina, magnesia, alkali oxides. With limestone, this slag can be used as a raw-material for manufacturing Portland cement clinker. This cement is not as reactive as OPC and during its first 28days, it gains strength at a slower rate. Hence, adequate curing is needed. This cement is mostly employed for mass concrete. The slag cement is more sulfate resistant compared to Portland cement (Nataraja and Nalanda, 2008).

2.2.1.2 Manufacture of Portland Cement

The basic materials for cement production are calcareous rocks (which contain $CaCO_3$> 75% such as limestone, marl, chalk), argillaceous rocks (which contain $CaCO_3$< 40% such as clay and shale), argillocalcareous rocks (which contain 40-75% $CaCO_3$ such as clayey limestone, clayey marl). Materials from any two of these may be used for Portland cement production providing that they must contain in proper form and proportions of lime, silica and alumina (Sutar, Patil, Chavan and Maske, 2021). The raw materials are contracted and mixed intimately. Supplementary materials are employed when there is deficiency of one of the ingredients.

Raw materials can be mixed and ground in either dry or wet conditions. The moisture content and hardness of the materials determines the method of production (Imbabi, Carrigan and McKenna, 2012). After quarrying in both processes when rock is the major raw material, primary crushing is the initial step. Using crushers, mountains of rock are fed. The rock is reduced to at most six-inches size during the first crushing, then it moves to the secondary crushers to atleast three inches. In the wet-process, the raw-materials properly proportioned are mixed with water, mixed thoroughly and fed into the kiln in the form of slurry. In the dry-process, raw materials are ground, mixed and released into the kiln in a dry-state (Sutar et al., 2021). In other words, the two processes are essentially alike.

The raw mix is heated to the point where water-content is evaporating as steam or water-vapor. The dried mix is heated to calcination temperature about 800 ^{o}C, such that the calcium carbonate in the mix is dissociated into calcium oxide, which remains in the mix, while carbon dioxide is driven off as gas. As the temperature rises during the heating of the mixture, the basic active compounds of Portland cement (calcium silicates, aluminate and aluminoferrite) are formed as the oxides of calcium, silicon, aluminum and iron react. This process is concluded at a temperature of 1400 ^{o}C and the resultant is Portland cement-clinker (Ali, Khan and Hossain, 2008).

The clinker is cooled and sent directly to the finish grinding mills. The grinding operation is done close to the using point. Clinker is ground to the specified fineness with the introduction of a little portion of gypsum to determine the setting time of the finished cement. The slag is also added during the grinding, when it is required (Paul, Van Rooyen, Van Zijl and Petrik, 2018).

Each phase in the production of Portland cement is examined by periodic chemical and physical test in plant laboratories. The last product is studied to ensure it conforms to all specification and is stored for a relative short time before being sent in bags to the customer. Figure 2.1 diagrammatically describes the process involved in the manufacture of Portland cement.

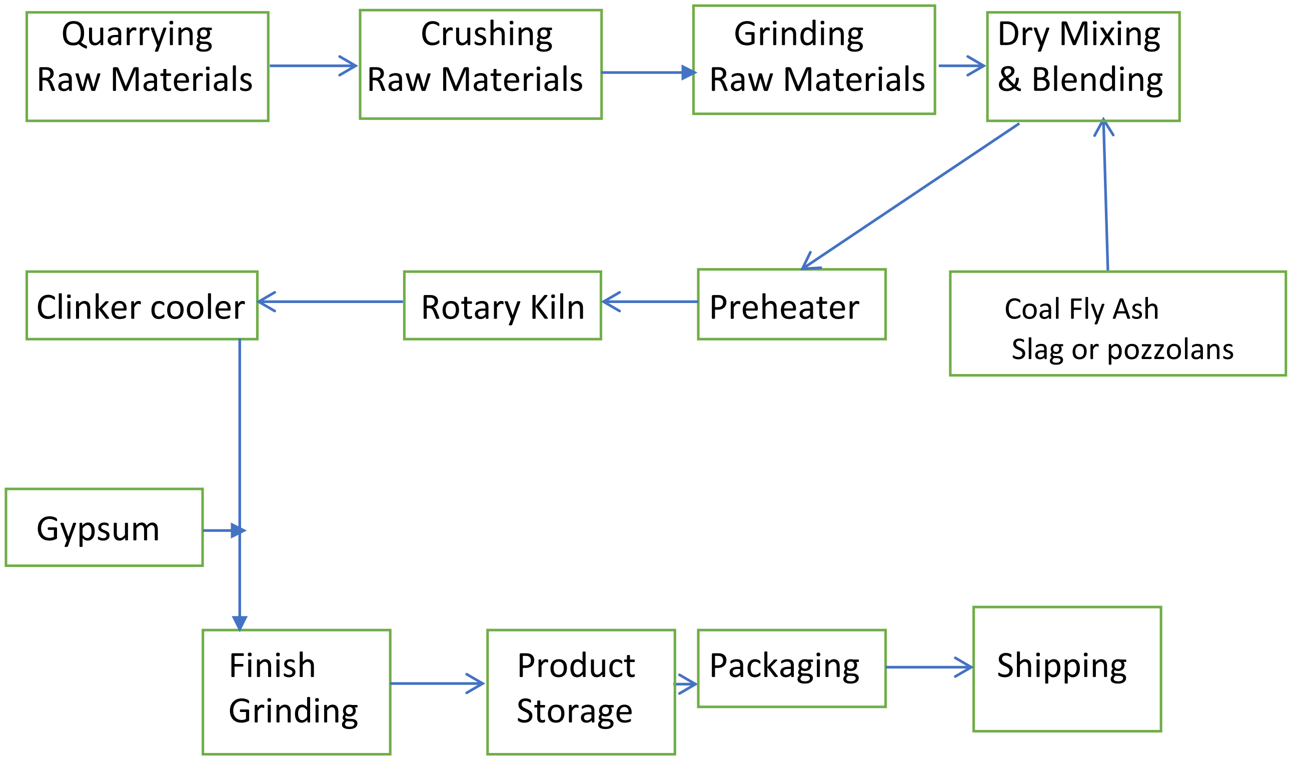

Fig 2.1: Process Flow Diagram of Cement Production

Source: Sutar et al., (2021)

2.2.1.3 Chemical Composition of Portland Cement

The oxides of silica, calcium, alumina and iron are the major raw materials adopted to manufacture Portland cement. They account for over 85% of the cement content. Table 2.1 describes the oxide composition of cement.

Table 2.1: The Oxide Composition of Ordinary Portland Cement

Common Name	Oxide	Abbreviation	Approximate Composition Limit (%)
Lime	CaO	C	56-62
Silica	SiO_2	S	12-22
Alumina	Al_2O_3	A	3-7
Iron Oxide	Fe_2O_3	F	1-4
Magnesia	MgO	M	0-4
Soda	Na_2O	N	0.3-1
Potash	K_2O	K	0.4-1
Sulfur Trioxide	SO_3	S	1-2

Source: Neville (1995)

Complex products are formed as these oxides interact with each other in the kiln. Table 2.2 shows a typical chemical description of ordinary portland cement.

Table 2.2: A typical Chemical Analysis of Ordinary Portland Cement

Item	Percentage (%)
CaO	63.1
SiO_2	20.9
Al_2O_3	5.6
Fe_2O_3	3.6
SO_3	1.3
MgO	2.5
K_2O	0.4
Na_2O	0.1
Loss on Ignition	1.2
Insoluble Residue	0.2
Free CaO	1.1
Total	100

Source: Ali et al., (2008)

Cement clinker is formed as different constituents merge during burning. The burning process generates compounds that can set and harden in the presence of water. These compounds are referred to as Bogue-compounds and they are as follows;

(i) Tricalcium Silicate ($3CaO.\ SiO_2$) C_3S

(ii) Dicalcium Silicate ($2CaO.SiO_2$) C_2S

(iii) Tricalcium Aluminate ($3CaO.\ Al_2O_3$) C_3A

(iv)Tetracalcium Aluminoferrite ($4CaO.\ Al_2O_3.\ Fe_2O_3$) C_4AF

Tricalcium Silicate (C_3S) occupies 35 to 65 % of the cement and its hydration is responsible for early strength development and it increases resistance to freezing and thawing (Vidican et al., 2008; Neville and Brooks, 2010). Dicalcium Silicate (C_2S) hydrates and hardens slowly and more time is required for it to contribute to strength (Akanni, Awofadeju, Adeyemo, 2014). Tricalcium Aluminate (C_3A) reacts with water rapidly and it is responsible for flash-set of finely-grounded-clinker. Its promptness is controlled by the introduction of little percentage of gypsum during grinding (Neville, 1995). Tricalcium-aluminate is responsible for the initial set, high heat of hydration and has greater tendency to volume changes causing cracking.

2.2.1.4 Physical Properties of Portland cement

The physical properties determine the quality of different brand of cements and such include its fineness, consistency, specific gravity, setting time, soundness, heat of hydration and strength (Shetty, 2005).

Fineness is the cement particle size and its evenness. It influences the rate of hydration and strength development. The finer cement becomes, the higher the hydration rate and strength (Ehikhuenmen, Igba, Balogun and Oyebisi, 2019; Hu, Ge and Wang, 2014; Mtarfi, Rais and Taleb, 2017). The specific gravity is applied in design of concrete mix proportion. Portland cement has a specific gravity of 3.15 while other types have specific gravities of 2.90 (Salem and Pandey, 2015).

When cement fails to shrink upon hardening, such ability is regarded as soundness. Without expansion, cement of good quality sustains its volume after setting due to the presence of free magnesia and lime. Consistency refers to the flowability of cement paste and this is measured with the Vicat-Apparatus (Mehta and Monteiro, 2006). When water is added to cement, it sets and hardens. Its setting time is dependent on its fineness and water-cement ratio (Elinwa and Mahmood, 2002; Gambhir, 2013).

The heat generated from the exothermic reaction when water is blended with portland cement is known as the heat of hydration. The hydration products (calcium hydroxide and calcium silicate hydrate), are mainly produced by the two calcium silicates (C_2S and C_3S). Tricalcium aluminate (C_3A) interacts quickly with water but can be delayed by introducing gypsum (Abbas and Majdi, 2017). C_3S contributes greatly to the development of cement-hydration, rheological attributes, the adsorption and dispersion of admixtures (Kumar, Bishnoi, Scrivener, 2012; Scrivener, Juilland, Monteiro, 2015; Cai, Xuan, Poon, 2022).

2.2.2 Aggregates

Aggregates are granular substances that gives form to concrete, defines its properties, including the economic impact of its production (Kabir, Aliyu, Nasara, Adamu, Chinade, Shehu, 2019). The internal structure, surface-nature and shape of aggregates largely affects concrete strength (Aginam, Chidolue, Nwakire, 2013). Aggregates occupies 80% of the concrete volume, hence its attributes greatly influence the properties of the concrete (Abdullahi, 2012; Naderi, and Kaboudan, 2021).

When subjected to grading through a set of sieves, materials passing the 4.75mm sieve openings are regarded as fine aggregates while those retained on it are called coarse aggregates (Kabir *et al.*, 2019; BS 882, 1992). Large quantity of natural aggregates is extracted for making concrete due to the enormous use of concrete daily. According to Eziefula, Ezeh & Eziefula, (2018), a careful evaluation of the world's expending of aggregate surpass 35 billion tonnes annually and between 60 and 70% of the mined aggregate is utilized for concrete. The reduction of natural resources such as aggregates, has raised the concern of jeopardizing the potential of next generation to feed herself (Fapohunda, Akinbile & Oyelade, 2008).

Due to the environmental hazards birthed by continuous extraction of these aggregates, there exist fixed restrictions (Imbabi, Carrigan & McKenna, 2012; Meyer, 2009). The search for sustainable replacement materials for aggregates in concrete has become the research goal of many scholars.

2.2.2.1 Classification of Aggregates

Aggregates can be categorized based on their;

(a) Geological origin

(b) Size

(c) Shape

2.2.2.1.1 Classification based on geological origin

On the basis of geological origin, aggregates are classified as follows;

i. **Natural Aggregates:**

These are products of crushed quarries of igneous, metamorphic or sedimentary rocks. Samples whose present size are reduced by natural agencies belong to this category. Aggregates originating from igneous rocks are the most widely used in concrete production (Singh, 2008). Those obtained from pits or water bodies will require sieving and adequate washing before being used.

ii. **Artificial Aggregates:**

These are mostly by-products or solid wastes of industrial processes or man-made construction materials, prepared by granulation. Consolidating solid particles of 1 - 450μm size ranges into larger sizes of 2 mm to 8 mm is known as granulation (Ren, Ling and Mo, 2021). Artificial aggregates include fly ash, granulated clay, husks, recycled concrete fines, broken bricks, blast furnace slag and broken glass (Mamlouk and Zaniewski, 2006).

2.2.2.1.2 Classification based on size

This include;

i. **Coarse Aggregates:**

These are granular materials derived from natural disintegration of rocks, retained on 4.75mm (BS 882: 1992), whose size is dependent on the section thickness, reinforcement spacing, cover, mixing and placing technique. Sizes above 20 mm are rarely adopted for reinforcement of structural concrete. Several scholars (Beshr, Almusallam, Maslehuddin, 2003; Aginam et al., 2013; Bhavya and Sanjeev, 2017; Khaleel, Al-Mishhadani, Abdulrazak, 2011; Kabir, Aliyu, Nasara, Chinade, Shehu, 2019) have carried out studies on the impact of these aggregates on concrete performance.

ii. **Fine Aggregates:**

These materials often referred to as sand are not larger than 5mm (BS 882, 1992; Naderi, and Kaboudan, 2021). Different researchers (Ekwulo and Eme, 2017; Abdullahi, 2012, Ajagbe, Tijani, Arohunfegbe and Akinleye, 2018) have investigated on the use of these aggregates for concrete production.

2.2.2.1.3 Classification based on shape

Classification based on shape, yields the following;

i. **Rounded Aggregates**

Basically, they are obtained from the river or sea shore and produce few voids of about 20% in the concrete. They have minimum ratio of surface area to the volume, and the cement paste required is little (Abdullahi, 2012). They are unfit for high-strength-concrete and pavements because of poor interlocking-bond.

ii. Irregular Aggregates

These materials have voids of about 40 % and needs more cement-paste compared to rounded aggregate. The inconsistency in shape, makes them possess good bond and are suitable for making ordinary concrete.

iii. Angular Aggregates:

They have sharp, angular and rough particles with maximum voids of over 45 %. Angular aggregates provide very good bond than rounded and irregular aggregates and are most suitable for high-strength-concrete and pavements. Their particles have their dimensions approximately same are called cubical aggregates (Ding, Li, Wu, Gao, Su, Sun,2020).

iv. Flaky Aggregates:

They are sometimes wrongly called elongated aggregates. However, both of these influence the concrete properties adversely. The least lateral-dimension of flaky-aggregate should be less than 0.6 times the mean-dimension. Elongated aggregates are those aggregates whose length is 1.8times its mean-dimension (Shetty, 2005). Flaky-aggregates generally orient in one plane with water-air-voids underneath. They adversely affect durability and are restricted to maximum of 15percent. Example of Flaky-aggregates are laminated rocks. Flaky/elongated aggregates make poor concrete.

2.2.2.2 Aggregate gradation

The grain-size distribution of aggregates in relative proportions as ascertained by sieve analysis is termed as grading of the aggregates (Abdullahi, 2012). More voids are contained in a compacted mass if all the aggregate' particles are of same-size, while there will be a mass with smaller voids for aggregates of varied-sizes. The voids between the larger particles are filled by smaller particles in the distribution. Dense-concrete with little amount of fine aggregate and cement waste are produced in a proper aggregate grading (Pawar, Sharma and Titiksh, 2016). Well-graded aggregates yield workable concrete mix and a concrete not susceptible to bleeding, segregation and shrinkage.

Through aggregate gradation, the void-content within the aggregate's structure is evaluated as well as the amount of cement-paste that is needed to fill the void-space in order to ensure a workable concrete (Naderi, and Kaboudan, 2021). Optimization of aggregate-gradation improves the rheological and mechanical properties of concrete (Crouch, Pitt, Hewitt, 2007; Pawar, Sharma and Titiksh, 2016).

2.2.2.3. Types of Aggregate Grades

There are different grades of aggregates. This include; well, uniform, dense, open and gap graded aggregates.

Various amount of larger and smaller particles is captured in well-graded aggregates. The smaller particles fill the voids between the larger particles which makes a dense, tight and stable concrete. In uniform-graded aggregate, all the particles are of equal narrow range of size with grain to grain content and large void content which makes it hard to compact (Pawar, *et al.,* 2016).

Dense-graded aggregate contains nearly equal quantity of different aggregate sizes with low void content and permeability. Very little number of aggregate particles in the small range are seen in open-graded aggregate and they have more air-voids. Gap-graded aggregate have only a little portion of aggregate-particles in the mid-size range with moderate void content and easy to compact (Chen and Liu, 2004).

2.2.2.4 The Grading Curve

A graph or an S-Curve is used to illustrate the grading of aggregates. The plot which depicts the collective percentages of the material passing the sieves shown on the ordinate with the sieve-openings to the logarithmic-scale represented on the abscissa is called Grading Curve. The grading curve for a particular sample shows whether the distribution of the particles conforms to that specified, or it is too coarse or too fine, or deficient in a particular size (Ajagbe, et al., 2017).

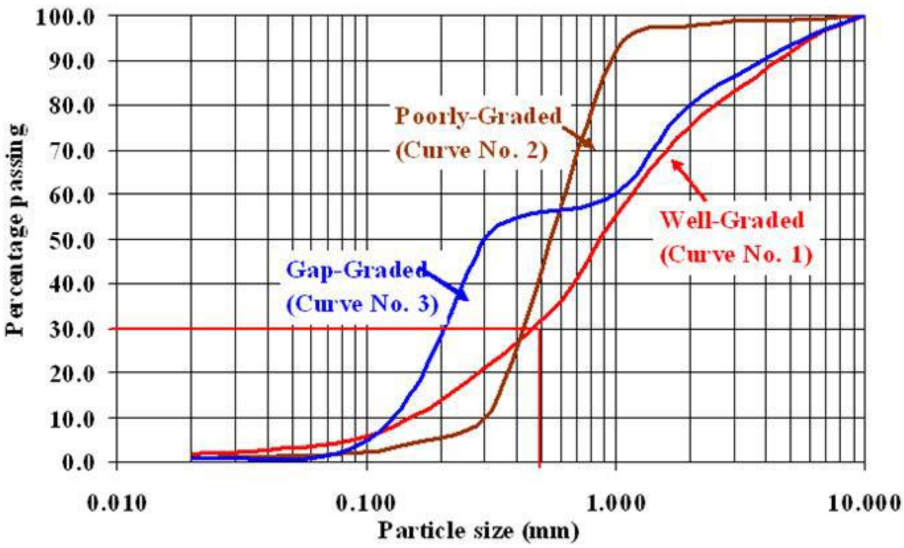

Fig. 2.2 Aggregate gradation curve

Source: Pawar, *et al.*, (2016).

2.2.3 Water

This is an indispensable concrete constituent that actively take part in the chemical reaction with cement. The amount and attribute of water is to be examined thoroughly as it directly affects concrete strength. Water that is fit for drinking is suitable for producing concrete (Neville and Brooks, 2010; Mama, Nnaji, Onovo and Nwosu, 2019).

The presence of chlorides, micro-organisms, salts of sodium, calcium and manganese available in mixing water will not only influence concrete strength and setting-time, but also my influence durability and corrosion of reinforcement (Mama et al., 2019). Addition of water with a cementitious material forms a cement paste by the process of hydration. The cement-paste glues the aggregates together, fills voids within it, and makes it flow more freely. Small water-to-concrete-ratio will yield a stronger and more durable concrete, while more water will give a freer flowing concrete with a higher slump (Olugbenga, 2014). Hydration involves discrete reactions often happening at the same period. As the reactions proceed, the products of the cement hydration process gradually bond together the individual sand and gravel particles and other components of the concrete of form a solid mass.

2.2.4 Admixtures

These are natural or artificial chemicals or materials added to concrete before or during mixing (Dumne, 2014). Admixtures are optional concrete ingredients. They modify properties of concrete according to required need. Appropriate application of admixtures gives certain advantageous effects to concrete such as; desired quality, acceleration or decline of setting-time, enhanced frost and sulphate resistance, early strength-development, improved workability and finish ability (Mahajan and Harle, 2017; Gambhir, 2001; Al-Gburis and Yusuf, 2022).

According to Shetty (2005), there are two types of admixtures;

i. Chemical admixtures

ii. Mineral admixtures

2.2.4.1 Chemical Admixtures

These admixtures are of various types and they include; accelerating, retarding, plasticizers and super-plasticizers admixtures.

The rate-of-hydration of hydraulic-cement and concrete strength increases with the application of accelerating admixtures while the opposite is the case when retarding admixtures are introduced (Lu and Ying, 2019). For difficult or special jobs and hot weather conditions, where delayed hardening is needed, retarding admixtures is applied (Xiaogang, 2013).

With the use of plasticizers, improved workability of plastic concrete is achieved without a reduction of the compressive strength at any given or desired water-cement ratio. They mostly depend on aggregate type and cement content (Gambhir, 2001; Na, 2017).

Super-plasticizers are high range water reducers and are employed for high-strength, ready mix, self-compacting concrete production (Akiije, 2019). They enhance quick de-molding, offer greater resistance to thawing and freezing, have little or no tendency to bleeding and segregation (Dabai, Muhammad, Bagudo, and Musa, 2009; Alsadey, 2012).

2.2.4.2 Mineral Admixtures

Mineral admixtures are of different types and they include grouting, air-detraining, waterproofing, bonding, corrosion-inhibiting, colouring and pozzolana admixtures.

Water-flow through the natural-capillaries in hardened concrete is blocked with the use of waterproofing admixture. They are mostly applied in water-retaining structures. Air-detraining admixtures such as tributyl phosphate and silicones, are employed to disperse excess air and other gases from fresh concrete. To grow the bond strength of old and new concrete, bonding admixtures which are water emulsions made from natural and synthetic rubbers such as polyvinyl-acetate, acrylics, styrene butadiene, are added to cement and applied to concrete surface before placement of plastic concrete.

The resistance of reinforcing steel to corrosion is increased with the aid of corrosion-inhibiting admixtures. This helps to improve the integrity and quality of reinforced structures (Abdulrahman and Ismail, 2012; Jayant, 2013). For aesthetics and safety reasons, colored admixtures are introduced to concrete. Most buried electrical or gas lines use red-concrete as warning tool to ensure safety.

Pozzolanic admixtures are siliceous-aluminous materials that possess cementitious properties (Setina, Gabrene and Juhnevica, 2013). Materials that serve as admixtures could be natural or artificial. Natural pozzolana include; clay, shale, diatomaceous earth, volcanic tuffs, opaline cherts, etc. Artificial pozzolana include; fly ash, blast furnace slag, silica fume, rice husk ash, metakaoline, bambara nutshell ash, sugarcane bagasse ash, sawdust ash, corncob ash and cassava peel ash (Alaneme, Olonade and Esenogho, 2023; Memon, Javed and Khushnood, 2019; Aprianti, Shafgh, Bahri and Farahani, 2015).

2.3 Application of Cassava Peel Ash in Concrete Production

The effect of partial replacement of cassava-peel-ash as investigated by Ofuyatan, Ede, Olofinnade, Oyebisi, Alayande, Ogundipe, and Olowofoyeku (2018), revealed that at 10% replacement, concrete’s durability and sulphric acid resistance considerably improved. The authors did not employ any mathematical model for optimization. Also, the cassava-peel-ash was not nanosized and 1.5% interval replacement was not considered.

The outcome of the study carried out by Raheem, Arubike, and Awogboro (2015), revealed that cassava peel ash (CPA) replacement of 5%, 10% and 15% has no significant reduction in strength compare to the zero-replacement sample. To produce the ash, they employed open burning, calcination and sieving with 150 µm sieve size. There was no form of nanosization in their study. No modelling technique was considered.

Salau, Ikponmwosa, and Olonode (2012), produced a blended concrete of mix 1:2:4 and used water cement ratios (w/c) of 0.5, 0.55, 0.6, 0.65 and 0.7. Their investigation revealed that increase of the replacement of CPA required more water for the blended concrete to be workable; hence considered w/c of 0.7 as the optimum. 15% CPA was concluded to be the best replacement level in the production of blended concrete. Second-degree polynomial regression was used for anticipating the compressive strength of cement-CPA blended concrete. The authors did not consider modelling with ANN neither was the ash nanosized.

Abdulwahab and Uche (2021), studied the durability-behaviour of self-compacting-concrete made with CPA and recommended 5% as the maximum cement replacement for grade 35 compressive strength of CPA-self-compacting concrete using 75 µm B.S. sieve to generate the ash. The CPA used was not nanosized and no form of modelling was employed by the authors.

Ettu, Ezeh, Ibearugbulem, Anya, and Njoku, (2013) developed mathematical models to vary concrete and sandcrete compressive strengths with curing periods and percentage replacement of ordinary-portland-cement and cassava-waste-ash. The authors used polynomial regression analysis for their results. The ash used by the authors was sieved through a 600µm sieve. There was no consideration for ANN modelling. The ash was not nanosized.

The study carried out by Olonade, Olajumoke, Omotosho, and Oyekunle (2014), investigated the effect of sulphuric-acid on strength of concrete whose cement was blended with cassava peel ash. The authors observed that the concrete produced, had relatively low compressive strength, when cured in sulphuric-acid and due to the leaching effect of the acid, sulphuric-acid-solution reduced the weight of cement-CPA concrete. Their study did not consider the use of nanosized ash and did not apply any modelling technique.

Owolabi, Popoola and Wasiu (2015), considered water cement ratios of 0.55, 0.60, 0.65 and 0.75 for the concrete mix 1:2:4 with 5% varying percentage of cassava-peel-ash (CPA) as replacement for cement at curing ages of 7, 14, 21 and 28 days. Their study confirmed that CPA, can be used optimally in concrete work by protracting the curing age as compressive-strength increases with curing age and decreases with increase in CPA content. However, the authors did not apply 1.5% varying percentage of CPA replacement neither was the CPA nano-sized. Also 56, 90 and 150days of curing was not considered. No form of optimization technique was employed by the authors.

2.4 Types of Concrete

There are numerous sorts of concrete, some of them can be applied for the same purpose, depending on the intended goal to be achieved. These include;

2.4.1. Plain Concrete

Plain concrete is concrete without any form of reinforcement in it, whose major materials are the cement, aggregates, and water. It uses the normal-mix design of 1:2:4. Its density vary from 2100 and 2400kg/m^3. Plain-concrete is often employed in the construction of structures where there is little or no need for high tensile strength (Singh, 2008). To some extent, its durability is satisfactory.

2.4.2. Reinforced Concrete

Reinforced-concrete contains steel bars, which is designed on the premise that both materials work together to withstand tensile forces (Mehta and Monteiro, 2006). Reinforced concrete is a blend of two dissimilar but complimentary-materials, namely concrete and steel (Oyenuga, 2011). It is often used in industries and modern structures. Its strength is enhanced by the placement of wires, cables or steel rods in the concrete before it is laid. These items are commonly known as reinforcing bars. Recently, fibers are being employed to reinforce concrete. While the concrete withstands compressive forces, the reinforcements resist tensile forces. They create a strong-bond and therefore both materials are resistant to a variety of applied forces. Basically, they become one structural element. Bridges, buildings, and roadways rely on reinforced concrete.

2.4.3. Prestressed Concrete

This type of concrete requires the exertion of inceptive compressive load on the material in order to minimize or terminate tensile interior forces, so that cracking is reduced. The prestressed member is greatly firm than the corresponding reinforced member when cracking is curtailed (Kong and Evans, 1999). Prestressed concrete units are applied in several big concrete projects. This concrete is formed using a unique approach.

Unlike reinforced concrete, the bars or tendons in prestressed-concrete are stressed prior to concrete application. As the concrete is being freshly made, the bars or tendons are kept at each end of the structural unit where they are used. When the concrete sets, this unit is put into compression. This process makes the bottom portion of the unit stronger against tensile forces. With prestressed concrete by tensioning the steel tendons, a pre-compression is introduced such that the tensile stresses during service are counteracted to prevent cracking (Mehta and Monteiro, 2006). Skilled labor and heavy equipment are needed in the pre-stressing process. The prestressing units are formed and assembled at the construction site. In the construction of heavy loaded structures, bridges and long span roofs; prestressed concrete is applied.

2.4.4. Precast Concrete

Using precise specifications, precast concrete is made, cast in the factory and brought to site when it is time to assemble them (Newman and Choo, 2003). Concrete blocks, precast walls and poles, staircase units, concrete lintels and many other structural elements are examples of precast concrete. The units made in the factory are exceptional and it has benefit of quick assemblage.

2.4.5. Lightweight Concrete

These are concrete that weighs less than about 1900kg/m^3 (Mehta and Monteiro, 2006). Lightweight aggregates produce lightweight-concrete. The density of concrete is determined by aggregate constituents. Pumice, perlites, scoria, clays, expanded shales and vermiculite are some of the examples of lightweight aggregates. The application of lightweight-concrete can be seen in the construction of building-blocks, long-span-bridge decks, and the protection of steel structures.

2.4.6. High-Density Concrete

Heavy weight coarse aggregates like crushed rocks are used to generate this type of concrete and its densities ranges from 3000 to 4000kg/m^3. They are also called heavyweight concrete. They are mostly applied in atomic-power-plants construction and similar projects as the heavyweight aggregates assists the structure to withstand various kinds of radiations (Newman and Choo, 2003).

2.4.7. Air-Entrained Concrete

Deliberately, air is entrained at 4 to 7% of the concrete. This is done by the incorporation of foams and gas-foaming agents such as fatty acids, resins and alcohols, with scrupulous inspection (Singh, 2008). This concrete is often adopted in a freezing environment or regions with freeze-thaw cycles.

2.4.8. Ready-Mix Concrete

This concrete is mixed and bathed in a centrally located plant and it is transferred to the site using a truck-mounted transit mixer. No further treatment is done to the concrete on arrival to site as it is fit for use instantly. Based on specifications, ready-mix concrete is a specialty concrete developed with great precision (Newman and Choo, 2003). A centralized location for concrete preparation is required for the making of ready-mix concrete and this location should be very close to the work-site.

2.4.9 Polymer Concrete

Polymer-concrete uses polymer as its binder. Polymer concrete comprises of polymer resins and micro-fillers. Compared with cement-concrete, they are more durable, stronger and with little maintenance requirements (Hameed and Hamza, 2018). Their distinct properties such as high mechanical strength, water impermeability, and good chemical resistance (Tawfikand and Eskander, 2006; Gorninski, Molin, and Kazmierczak, 2007) increases their applications in civil engineering works including construction of trench lines, box culverts, underground pipes, and industrial floors.

2.4.10 Smart Concrete

This is the concrete-technology of the future. It offers a unique way to monitor the condition of structures with reinforced concrete. Short carbon fibers are included to the concrete employing a concrete mixer. Electrical resistance of the concrete is affected when it encounters strain or stress. It can identify potential problems before the failure of the concrete (Gaurao, Ankush, and Archana 2016). Smart concrete is outstanding at recognizing mini structural defects.

2.5 Production of Concrete

Concrete is primarily a uniform blend of cement, coarse and fine aggregates and water which consolidates into a hard mass due to chemical action between the cement and water. Each of the constituents has a specific function. The coarser aggregate acts as a filler. The fine aggregate fills up the voids between the paste and the coarse aggregate. The cement jointly with water acts as a binder. The stages of concrete-production include batching, mixing, transporting, placing, compacting, finishing, curing, and formwork removal.

2.5.1 Batching

This is the process of measuring concrete-mix ingredients either by volume or by weight. The proportions of varying constituents are obtained from mix-design. A concrete-mix is designed to make concrete that can be easily placed at the lowest cost. The concrete must be workable and cohesive when plastic, then set and harden to give strong and durable concrete (Deligiannis and Manesis, 2008).

2.5.2 Mixing

The mixing operation consists of rotation or stirring, the objective being to cover the surface of all aggregate-particles with cement paste, and to bind all the ingredients of the concrete into a uniform mass (Bashandy, 2012). The mixing may be done by manually or by mechanical means like, Batch-mixer, Tilting-drum-mixer, Non-tilting-drum-mixer, Pan type mixer, Dual drum mixer or Continuous mixers.

2.5.2.1 Types of Concrete Mixes

According to CORBON (2014) concrete mixes is classified into three types of namely:

i. Nominal Mixes
ii. Standard/Prescribed Mixes
iii. Designed Mixes

2.5.2.1.1 Nominal Mixes

Basically, concrete specifications dictate the proportion of its constituents. Nominal mixes are those mix that ensures that required strength is achieved with an established aggregate to binder ratio. The common mix is usually 1:2:4. Water-binder ratio varies while cement and aggregate proportion is set. There is wide variation in strength for a given workability as a result of mutability of the ingredients (Anum et al., 2014).

2.5.2.1.2 Standard or Prescribed mixes

The nominal-mixes of fixed cement-aggregate ratio (by volume) vary widely in strength and may result in under- or over-rich mixes (Yunusa, 2011). For this reason, the minimum compressive strength has been included in many specifications. These mixes are termed standard-mixes. The engineer outlines a standard concrete mix-ratio that will create the desired concrete. The type and size of aggregate to be used is also indicated. Based on the ratio that has been stipulated, the mixes are prepared.

2.5.2.1.3 Designed Mixes

Concrete performance is defined by the mix-proportions. Mix design is most rational technique to selecting mix-proportions with specific materials in mind having more or less unique features. However, the designed-mix does not serve as a guide since this does not guarantee the correct mix-proportions for the prescribed-performance. Proportioning concrete based on the specified design mixes involves more steps and the use of tabulated data and charts. The approach births the production of concrete with the desired properties most economically. This is because the characteristics of the materials to be used and the characteristics of the concrete required are incorporated in the design procedure (Rosa, Hammad, Boer and Haddad, 2023). The design mix depends on proportions finalized using experimental tests. This will determine the strength needed based on the structural design of the concrete component.

2.5.2.2. Grade Designation

According to Yunusa (2011), every concrete has its strength in N/mm^2, psi, MPa, when subjected to test after 28 days of curing in any medium. The choice of concrete grade, depends on the purpose and usage as shown in Table 2.3 below:

Table 2.3: Concrete Grade Designation

Concrete Grade (N/mm^2)	Mix Ratio	Application
10	1:4:8	Blinding concrete
15	1:3:6	Mass concrete
20	1:2.5:5	Light reinforced concrete
25	1:2:4	Reinforced concrete/precast
30	1:1.5:3	Heavy Reinforced concrete/pre-cast
35	1.:1.5:2	Pre-stressed/precast Concrete
40	1:1:1	Very heavy reinforced concrete/pre-cast/prestressed

Source: (Yunusa, 2011)

2.5.3 Transportation

This is the conveying of ready-mixed concrete from the point where it is made to the job site (Mehta and Monteiro, 2006). This is done as quickly as possible to reduce stiffening to the point that after the placement, full consolidation and proper finishing become difficult. This stiffening and loss of consistency affect the quality of concrete produced.

2.5.4 Placing

This is the process by which plastic concrete is placed at the point where it is needed. Belt-conveyors, truck-mounted chutes and mobile-boom pumps are among the most-commonly-used today for concrete placement. When plastic concrete is moved over too long a distance during the placement into forms, there tends to be segregation and this affects the concrete quality (Mahzuz, Bhuiyan, and Oshin, 2020).

2.5.5 Compaction

Placing and compaction are inter-dependent and are done concomitantly. They are essential for the purpose of ensuring the requirements of impermeability, durability and strength of hardened concrete in the actual structure. The major aim of placing is to deposit the concrete as close as possible to its final position so that segregation is avoided and the concrete can be fully-compacted. Good concrete-placing gets the concrete into position at a speed, and in a condition, that allow it to be compacted properly. Once the concrete has been placed, it is ready to be compacted. The essence of compaction is to get-rid-of the air-voids that are trapped in loose concrete (Singh and Srivastava, 2017).

It is needful to compact the concrete fully because air-voids reduces the strength of the concrete. Air voids increase concrete's permeability. That in turn reduces its durability (Shetty, 2005). If the concrete is not dense and impermeable, it will not be watertight. It will be less able to withstand aggressive liquids and its exposed surfaces will weather badly. Moisture and air are more likely to penetrate to the reinforcement causing it to rust. Air-voids impair contact between the mix and reinforcement (and, indeed, any other embedded metals), hence the required bond will not be achieved and the reinforced member will not be as strong as it should be.

2.5.6 Finishing

This is the act of firmly embedding the concrete mixture, compacting the surface and removing any remaining imperfections. It is the process of producing dense surfaces that will remain maintenance free (Combrinck, Steyl, Boshoff, 2018).

2.5.7 Curing

Curing is the process of making the concrete surfaces wet for a certain time period after placing the concrete so as to promote the hardening of cement. This process consists of controlling the temperature and the movement of moisture from and into the concrete (James, Malachi, Gadzama and Anametemfiok, 2011). It controls the rate of moisture loss from concrete to ensure an uninterrupted hydration of Portland cement after concrete has been placed and finished in its final position. Curing helps maintain an adequate temperature of concrete in its early stages, as this directly affects the rate-of-hydration of cement and eventually the strength gain of concrete or mortars.

Curing is done after placement and finishing and is continued for a reasonable period of time, for the concrete to attain its desired strength and durability. Uniform temperature is maintained throughout the concrete depth to avoid thermal shrinkage cracks. If curing is efficient, the concrete-strength gradually increases with age (Zain, Sauddin and Yu-Sof, 2000). This increase in strength is sudden and rapid in early stages and it continues slowly for an indefinite period. By proper curing, the durability and impermeability of concrete are increased and shrinkage is reduced. Concrete's resistance to abrasion is considerably increased by proper curing.

According to James et al., (2011), different curing methods that can be employed for curing concrete are ponding, sprinkling, wet-covering, plastic sheet and open-air. Ponding was recommended as the best of curing methods as it produces the highest compressive strength and cube densities.

2.5.8 Removal of Formwork

This is the last operation carried out during the early age period of concrete. Concrete structures have failed when forms were stripped before concrete had attained sufficient strength (Mehta and Monteiro, 2006).

2.6 Engineering Properties of Concrete

Among the various engineering properties that concrete possess, few were considered herein. They include; compressive strength, workability, durability, impermeability, modulus of elasticity, creep and shrinkage.

2.6.1 Compressive Strength

Strength is resistance to rupture (Shetty, 2005). Strength can be measured in terms of compression, tension, flexure, or shear, with reference to a particular method of testing (Ayeni and Ayodele, 2015). Concrete has relatively high-compressive-strength, but significantly lower tensile strength, and as such is usually reinforced with materials that are strong in tension (often steel). This is the most important character of concrete.

The characteristic strength, that is the concrete grade, is measured by the 28-day cube strength. Major factor affecting the strength-of-concrete is the water-cement ratio. This effect according to Shetty (2005) is supported by Abrams water/cement ratio law, which states that concrete’s strength is only dependent upon water-binder ratio provided the mix is workable. Other factors affecting compressive strength are, curing periods, proportion of cement to aggregate, grading, surface texture, shape and size of aggregate particles (Aginam, Chidolue and Nwakire, 2013; Bamigboye, Ede, Umana, Odewumi, and Oluwu, 2016; James, Malachi, Gadzama, and Anametemfiok, 2011). Concrete with a lower water/cement ratio is stronger than that with a higher ratio (Salem and Pandey, 2017). The total quantity of cementitious-materials can affect strength. It is essential that freshly-mixed concrete be thoroughly consolidated to eliminate air-pockets and secure maximum density in the structure.

The degree of curing and protection afforded after placement is highly important to the final strength attained by the concrete. Concrete-strength varies with time, and the specified concrete strength is usually that strength that occurs 28 days after the placing of concrete. Specification for different class of concrete according to British standards is as shown in Table 2.4.

Table 2.4 Characteristic Compressive Strength for Structural Concrete

Grade	Characteristic Strength (N/mm^2)	Concrete Class
7 10	7 10	Plain Concrete
15	15	Reinforced concrete with lightweight aggregate
20 25	20 25	Reinforced concrete with dense aggregate
30	30	Concrete with post tensioned tendons
40 50 60	40 50 60	Concrete with pre-tensioned tendons

Source: BS 8110: 1997

2.6.2 Workability

Workability is the ability to manipulate (placing, compacting and finishing) a freshly-mixed quantity of concrete with minimum loss of homogeneity. The properties of fresh concrete that expresses workability are compatibility, mobility and consistency. The measure of fluidity is considered as consistency while compatibility is the ease with which voids, entrapped air, and segregation can be removed from a mix. Mobility is the ability of fresh concrete to move into a prepared formwork (Rawarkar and Ambadkar, 2018).

Constructability depends on workability. Workability is determined by admixtures, water content, aggregate-cement ratio, size, shape, grading and surface texture of aggregates (Jain, Jain and Sancheti, 2021), A workable concrete is one that can be easily placed and compacted uniformly without bleeding or segregation. According to Mehta and Monteiro (2006), bleeding is a phenomenon whose external manifestation is the appearance of water on the surface after a concrete mixture has been placed and compacted but before it has set (when sedimentation can no longer take place) while segregation is the detachment of components of a fresh concrete mixture so that they are no longer uniformly distributed.

2.6.3 Durability

The ability of concrete structure to retain its safety, normal application and desired appearance under varied environmental states without the need for extra maintenance costs for reinforcement treatment within its specified service life, is referred to as durability (Wang, Wu, Chen and Zeng, 2020). Different concretes require different durability design, depending on the environment and features desired. Appropriate concrete ingredients, mix proportions, finishes and curing practices can be adjusted on the basis of required durability of concrete.

2.6.4 Impermeability

One of the primary indicators of concrete durability is impermeability. The resistance of concrete to water-flow through pores is regarded as impermeability. The microgeometry and porosity of pore structures of concrete determines its permeability resistance (Zhang, Gao, Wang, Guo and Wang, 2022; Wang, Zhou, Shi, Huang, Zhao, Huo, and Tang, 2022). Permeability in concrete are mostly influenced by water-cement ratio, compaction and curing.

2.6.5 Modulus of Elasticity

Modulus of elasticity of concrete expresses the stress-strain relationship in the elastic range and it is employed in the prediction of concrete elements. It is applied in the evaluation of shrinkage, creep, cracking and in seismic analysis for rational deformation and drift computation. Composition of concrete mix, aggregate size, concreting technique and curing method influences the elastic modulus of concrete (Sadowski and Jaskulski, 2018). The knowledge of this mechanical property of concrete is required for estimation of structural deformations under service conditions in prestressed, reinforced concrete and in mass concreting (Yazdi, Kalantary and Yazdi, 2012).

2.6.6 Creep

The deflection of concrete structures under sustained load is referred to as creep. The shape of these structures changes under long-term pressure or stress. Aggregate properties, quantity of cement paste, size of concrete specimen, concrete strength, curing conditions and age of concrete, determines the magnitude of creep experienced by the structural elements (Kim, Kwon, Kim and Kim, 2005). Different scholars have studied creep effect adopting varied loading level, direction including loading age (Kammouna, Briffaut and Malecot, 2019), and more studies are ongoing as regards the impact of creep on the mechanical properties of concrete.

2.6.7 Shrinkage

The evaporation of water not used for hydration during concrete curing often result to shrinkage. Shrinkage often lead to concrete cracking which disfigures structural surfaces and jeopardizes the durability as ingress of water, carbon dioxide and other aggressive materials are facilitated. Shrinkage depends on the aggregate properties, mechanism of cement paste, and behaviour of water movement. Concrete shrinkage is mainly driven by cement paste (Maruyama, Sasano and Lin, 2016). Intense research attention is drawn on the behaviour of concrete due to shrinkage.

2.7 Nanotechnology in concrete

Concrete is the most ubiquitous structural composite-material that is nano-structured and multi-phased (Sanchez and Sobolev, 2010). It has an amorphous phase, nanometer- to micrometer-size crystals and bound-water. Either at the interfaces between liquid–solid and solid–solid, or at the solid and liquid phases of concrete, are the locations that nano-engineering can take place (Garboczi, 2009).

Nanotechnology is a unique engineering field connected with the study of matter at the nanoscale, whose dimensions are approximately between 1 and 100 nm. Properties of materials are clearly examined at nanoscale. Ji (2005), observed that the behaviour of concrete and the size of calcium silicate hydrate phase responsible for strength-gain is captured fully in the nanometer zone.

Studies carried with nanosilica, nanoiron, nanoalumina, and nanoclay particles in concrete showed that incorporation of nanomaterials into concrete matrix improves its mechanical properties, due to the high surface area-to-volume ratio of the nanoscale particles (Bjornstrom et al., 2004; Flores, 2010; Ji, 2005).

According to Sanchez and Sobolev (2010), there are two approaches to the nanoscale; the top-down and bottom-up approach which respectively refers to size reduction from large to small and production of materials using molecular or atomic components. This study followed the approach of size reduction. The cassava peel ash adopted in this work, was nanosized.

2.8 Optimization

The concept of optimization is referring to obtaining the best effect or element from available alternatives, that meets a set of specification (Snyman, 2005; Chinneck, 2007; Simon 2003). Optimization of concrete properties is therefore the process of selecting the most suitable concrete ingredients that produces the possible optimum concrete properties in terms of durability and strength. In order to achieve the choicest, several responses are considered simultaneously. However, appropriate model that can perform this must be established.

2.9 Methods of optimization

Several optimization techniques evolved in order to solve the problem of concrete mix proportions and cost of concrete production. Optimization can be carried out using either statistical models or machine learning models.

2.9.1 Statistical Models

Statistical models such as Scheffe's, Osadebe, Ibearugbulem's approach, axial designs, process variables, orthogonal block designs inverse terms, inert components, log contrast models, mixtures with additive effect and K-models, have gained more attention among researchers.

2.9.1.1 Scheffe's Model

Scheffe's model is based on simplex lattice and simplex theory (Oba, Ugwu and Okafor, 2019). The simplex-lattice is an ordered arrangement of line joining the assumed experimental points of the mixture ingredient proportion design (Akeke, Nnaji and Udokpoh, 2021). Scheffe's theory states that the factor space for mixture experiment is a regular $(q - 1)$ dimensional simplex and for the mixture, the sum of the constituents of the mixture is not greater than 1 (Attah, Etim, Alaneme, Bassey, 2020). Several authors such as (Akobo, Akpila, and Okedeyi, 2020; Mama and Osadebe, 2011; Oba et al., 2019), have applied this model in concrete mixture research.

2.9.1.2 Osadebe's Model

Osadebe's model is based on the principle of absolute volume (Onwuka and Sule, 2017). Consider a five-component concrete mixture to have a total quantity, S and the proportion of the ith component as Si. Osadebe, Mbajiorgu and Nwakonobi (2007), assumed the response function, f(Z) to be continuous and differentiable with respect to its predictors Z_i. The function f(Z) can be expanded in Taylor's series in the neighborhood of a chosen point $z^{(0)}$.

2.9.1.3 Ibearugbulem's Model

Although Scheffe's and Osadebe's models are appropriate for optimization of concrete mix, they are greatly limited in that the fixed experiments must be carried out in order to develop them and they can only be applied for mix ratios that fall within the fated observation points. Ibearugbulem's model was formulated as a new model to overcome the inherent problems in previous models (Ibearugbulem, Ettu, Ezeh, Anya, 2013). The conception began with Osadebe's procedure. Scheffe's and Osadebe's constraints were later imposed on it. Some modifications were made to obtain the model. This model has been thoroughly examined through concrete laboratory experiments (Ibearugbulem, Amanambu, Elogu, 2014).

2.9.2 Machine Learning Models

Statistical approaches are commonly employed in the optimization of concrete mixtures. Despite their prediction suitability, research attention has been drawn to their drawbacks. Machine learning models were developed to address these shortcomings. These methods are also called artificial Intelligence method. In recent years there has been an increasing number of studies and applications of intelligent systems in civil engineering. These methods include; Genetic Algorithms (GA), Fuzzy Logic (FL), Adaptive Network Based Fuzzy Inference

System (ANFIS) and Artificial Neural Networks (ANNs). The focus in this study is mainly on artificial neural networks and its application in prediction of compressive strength of nanosized cassava peel ash-cement concrete, some soft computing methods are discussed below.

2.9.2.1. Fuzzy logic

This is a multi-valued-logic computational model that is efficient and effective at implementing non-linear mapping between the output and input variables, analyzing truth value stipulation of a complex logical postulation by the truth value of its components and its varying degrees of truth; in an approximate intelligent approach rather than being exact or fixed (Kim and Heeyoung, 2016; Alaneme and Mbadike, 2021; Madadi, Tasdighi, and Eskandari-Naddaf. 2019; Topcu and Sarıdemir 2008). Excellent models with optimum prediction accuracy for concrete mixture can be achieved using Fuzzy Logic concept (Aryafar, Mikaeil, Doulati, Shaffiee-Haghshenas, and Jafarpour, 2018).

2.9.2.2 Adaptive Network-based Fuzzy Inference System (ANFIS)

ANFIS combines the learning ability of the ANN and the smart evaluation technique of fuzzy logic system to solve complex optimization problems. Basically, ANFIS employs back-propagation gradient descent as its learning rule and hybrid learning approach which applies least squares method and gradient-descent method to ascertain the required adaptive parameters (Ramezanianpour, Sobhani, and Sobhani, 2004; Jang, 1993). The model simulation, training, testing and validation of the mechanical behaviour of concrete can be achieved using the ANFIS computation toolbox in MATLAB software.

2.9.2.3 Genetic Algorithm

Genetic algorithm is a global search and optimization model inspired by genetic variation and natural selection which offers optimal solution for varying problems in machine learning (Pendharkar, 2019; Chandwani, Agrawal and Nagar, 2014). Historical information is used to formulate new offspring with desired improved performance. It is often integrated with ANN in different fields of study (Irani and Nasimi, 2011)

2.9.2.4 Artificial Neural Network (ANN)

Artificial neural network (ANN) is an information processing model stimulated by the learning ability of the human brain (Awodiji, Onwuka, Okere, Ibearugbulem, 2018). ANN consists of many highly interconnected elements known as neurons, working together to resolve specific issues. By a learning process, ANN is structured for a peculiar application, such as model recognition or data classification (Sebastia, Fernandez, and Irabien, 2003). Learning in biological systems involves fitting into the synaptic connections between neurons. The same applies to ANNs.

In general, neural networks are adjusted or formed, such that a particular input results to a specific target output. The network is adjusted based on a comparison between the output and the target, until the network output meets the target (Kiran and Lal, 2016). To represent and capture complex input-output relationships, ANN is a computational powerful tool that can be used (Ayat, Kellouche, Ghrici, and Boukhatem, 2018). Apart from structural engineering, different research fields such as geology, medicine, and physics have employed ANNs (Zhang et al., 2019; Sadowski et al., 2019; Pala et al., 2018).

ANN easily models the non-linear complex relationships with vast number of interconnected elements involved in the estimation of the output parameter and the simulations are performed in MATLAB environment using the neural network toolbox (Twomey and Smith. 1997; Topcu and Sarıdemir,2008). In ANN, information is processed or stored throughout the network simultaneously, instead of specific locations; i.e. the processing and location of the data is in the global and not localized. The neurons of ANN are connected by links through weighted parameter in order to pass signals from one neuron to another and through the neuron's output connection to the next neuron, the output signal is transmitted through a number of branches which terminates at the input connections of the next in the network (Basma and Kallas,2004).

Among other available prediction tools, ANN is the most commonly employed method by many scholars. The model is predicated on numerous input and single output whereas regression models involves single input and output that determines the scatter of measured input from the output. The ANN is the antidote for multi-dimensional problem. The strength model based on the ANN is more exact than the regression-based model (Thandavamoorthy, 2015).

2.9.2.4.1 ANN Architecture

The network architecture is the setting of processing elements to form layers and the connection pattern formed within and between the layers (Fausett, 1994; Mohammadhassani, Nezamabadi-Pour, Jumaat, Jameel, Arumugam, 2013). A layer is formed by taking a neuron and joining it with other neurons. The arrangements of these neurons and geometry of their interconnections are crucial for an ANN.

There exist basically five types of neuron connection. They include; single node with its own feedback, single-layer feed-forward, multilayer feed-forward and single-layer recurrent, multilayer recurrent network (Fausett, 1994; Lai and Sera, 1997; Kartam, Flood, Garrett, 1997; Khademi, Jamal, Deshpande, Londhe, 2016; Yilmaz and Yuksek, 2009).

2.9.2.4.2 ANN Learning

The production of target response due to the adaptation of neural network to a stimulus is referred to as learning and the ability to learn is the major character of ANNs (Fausett, 1994; Ni and Wang, 2000; Trtnik, Kavčič, Turk, 2009). This adaptation is achieved when accurate parameter adjustments are made. The examples through which ANN learns, are collections of input and output representative of patterns of activation (Lee, 2003). Learning is achieved with ease when the input data has the exact information connected with the desired output (Paulson, Prabhavathy, Rekh, Brindha, 2019). Learning in ANN can be generally classified into three categories as supervised, unsupervised, and reinforcement learning (Nath, Goyal, Nath, 2011; Udhaya, Bharat, Balasubramanian, Krishna, 2007; Fausett, 1994; Kim, Kim, Feng, Yazdani, 2004).

2.9.2.4.3 Back propagation

Backpropagation is a supervised-learning algorithm extensively used in feed-forward multilayer-neural networks. ANN is trained with the input and target output vectors. The network and target output are often used to calculate the error data of the output layer. The error is back-propagated to intermediate layers, authorizing incoming weights to these layers to be revamped (Martin, Howard, Mark, 2002; Rumelhart, Hinton, Williams, Ronald,1986).

Application of backpropagation have drawn more attention among scholars due to its captivating attributes such as its simplicity in understanding and its competence in showing functional intermediate representations at the hidden unit layers.

2.9.2.4.3.1 Back propagation using gradient descent method

The minimum of a function and the minimum squared error between the network output values and the target, are obtained with the gradient descent, which is a first-order iterative optimization algorithm with steps that are proportional to the negative of the gradient (Snyman, 2005). When the model is trained to optimize the loss function using one particular example from the dataset, it is called stochastic gradient descent. When the model is trained to optimize the loss function using the mean of all the individual losses in the entire dataset, it is called Batch Gradient Descent.

2.9.2.4.3.2 Back propagation using Levernberg-Marquart method

LM algorithm is the most commonly used iterative and optimization technique used for training the network and locating a local minimum of a multivariate function which is expressed as the sum of squares of several non-linear and real-valued functions. It is widely applied in different disciplines for handling data-fitting applications (Martin and Mohammad,1994; Sivanandam, Sumathi, Deepa, 2008).

2.9.2.4.4 Activation Function

Computations carried out by the neural network is inspired by the activation function, which is responsible for the transformation of the net input into a neuron to the data the neuron transmits (Fausett, 1994). The values of activation function are a scalar quantity while the respective argument is a vector quantity. To ascertain whether or not to fire output signal, activation function computes the weighted sum of the input parameters including the bias and then compare the obtained result with the system's threshold value (Moosavi, Yazdanpanah, Doostmohammadi, 2006). There are several activation functions, which are identity function, binary step function, bipolar step function and sigmoidal functions. In back-propagation networks, the sigmoidal functions are widely used.

2.10 Application of ANN to Concrete Technology

Onwuka & Awodiji (2013) employed feed-forward back-propagation neural network to predict the modulus of rupture of concrete. The authors used 400 data and 67 data for training and testing the ANN model respectively. Traingdm and Learngdm served as the training and learning function respectively.

Khan, Ayub, Rafeeqi, (2013) developed ANN model for compressive strength of concrete confined with ferrocement, using multilayer-feed-forward neural network. The result of the model was equivalent to the experimental outcome

Duan, Kou and Poon (2013) used ANN modeling to predict the compressive strength of recycled aggregate concrete (RAC). Back-propagation neural network was employed for modeling the compressive strength with fourteen input parameters and one output parameter. ANN model is constructed using 146 available sets of data obtained from 16 different published literatures. The study showed the applicability of ANN for modeling the compressive strength of concrete containing of recycled aggregates which have composition and properties substantially different from natural aggregates.

The outcome of the ANN model and regression analysis done by Das, Pal, and Singh (2015), revealed that prediction of cement and water content is easier compared to investigating on the quantity of aggregates. The maximum percentage error derived from the ANN model was less than 1%, which demonstrated the adequacy of the model.

ANN model was developed with three-layered feed-forward neural network and a back-propagation algorithm by Ogbodo & Dumde (2017) to predict concrete mix ratio. The results obtained from their study revealed the excellency of ANN.

Reinforced concrete elements were examined by Chandan, Raghu, and Amarnath (2017) using ANN. The analytical values of the displacements, shear and moments were compared with the values of ANN model. The two were observed to be in close range.

ANN model was developed by Awodiji, Onwuka, Okere and Ibearugbulem (2018) to predict the compressive strength of hydrated lime-cement concrete using some selected mix ratios Their study showed that the concrete can be used if the cement replacement was not up to 30%. The network results were in conformity with the experimental outcome. The value obtained from the student’s T-test proved the reliability of the network prediction.

2.11 Summary and Gaps in Literature

The relevance of cassava peel ash (CPA) for partial replacement of ordinary Portland cement cannot be overemphasized. However, more works need to be done for uncovered areas. And one of such areas yet to be investigated is the use of CPA for production of Nano-concrete. Hence this research work is needful.

In previous studies, several authors used 75 µm and 600µm sieve. Particles passing the sieve were used. The particle size of CPA used were less than 600µm(0.6mm) which is more compared to the particle size of OPC which lies between 7µm to 200µm (0.007mm to 0.2mm). Nanosizing the cassava peel ash with 200nm nano sieve, makes the pozzolanic material (CPA) finer than cement particles. The use of this finer particles from nanosized cassava peel ash (NCPA) has advantages in terms of filling the cement matrix and densifying the structure thereby resulting in higher strength and faster hydration. This gap in literature is worth filling.

In contrast to previous works (Salau *et al.* 2012; Ettu *et al.* 2013; Olonade *et al.* 2014; Raheem *et al.* 2015; Owolabi *et al.* 2015; Ofuyatan *et al.* 2018; Abdulwahab and Uche 2021), the distinguishing feature of this present study is the particle size of cassava peel ash, percentage interval of partial replacement, curing age and method of optimization model employed. Unlike the previous works that used polynomial regression analysis, the present work applies a soft computing technique for optimization modelling. To the best of my knowledge, there is no work on nanosized cassava peel ash (NCPA) cement-concrete using artificial neural network (ANN) method. The peculiarity of this study is quite clear and cannot be neglected, as it is worthwhile to fill this gap in the literature. The focus of this study is to investigate experimentally the compressive strength of NCPA-cement concrete and formulate an ANN model that can be used to predict the strength.

CHAPTER THREE

MATERIALS AND METHODS

3.1 Materials

The materials employed in this study include: Portland Cement, Nanosized Cassava Peel Ash, water, river-sand, and coarse aggregate. Each of these materials is discussed.

3.1.1 Portland cement

The *BUA* brand of Portland Cement that is in accordance with the specification of BS 12 (1996) was used. The BUA cement is a CEM II type of cement with strength grade 42.5 R and specific gravity of 3.04.

3.1.2 Nanosized Cassava Peel Ash

Cassava peels were fetched from cassava peels dump-sites at Umuofeke and Obeama in Ohaji-Egbema L.G.A in Imo State. NR (8082) and NR (8083) were the major improved cassava varieties cultivated by the farmers in the location. These varieties were preferred due to some benefits such as early maturity and increased yields. The cassava peels were assembled and sun-dried. The cassava-peel was calcined in a kiln at a temperature of about 700 ^{0}C in 60 minutes in a control combustion set-up to avert befouling. The torrefied material was collected and sieved scrupulously with a nano-sieve of size 200nm, to yield fine nanosized ash. The specific gravity of the nanosized ash was found to be 2.11. The nanosized cassava peel ash (NCPA) has a meagre specific gravity when juxtaposed with the specific gravity of cement (3.04). This inferred that partially replacing OPC with NCPA will result to reduced weight of concrete members. The NCPA is 1.4 times lighter than cement.

Plate 3.1. Cassava Peels Sun Dried

Plate 3.2 Nanosized Cassava Peel Ash

3.1.3 Water

The water used for the experiment during mixing and curing operation was fit for drinking and it conformed to the stipulations in BS 3140 (1980). Portable water was obtained from the borehole at the concrete laboratory, civil engineering department, Federal University of Technology, Owerri.

3.1.4 Aggregate

Two sets of aggregates were employed in this study, namely;

(i) Fine aggregate:

The sand used in this work was obtained from Imo River, Imo State of Nigeria. It was sieved through 10mm British Standard test sieve to remove cobbles to satisfy the requirements of BS 882 (1992). It has physical properties of 2.65 and 2.92 corresponding to its values of specific gravity and fineness-modulus respectively. The river-sand is uniformly graded because it has coefficient of uniformity and coefficient of curvature values of 2.70 and 0.96 respectively.

(ii) Coarse aggregate:

The crushed granite used in this study was sourced from the quarry-site at Ishiagu, Ebonyi State, Nigeria. The maximum size of aggregate used for this work is 20mm diameter. It conformed to the requirements of BS 882 (1992). It has physical properties of 2.65 and 3.28 corresponding to its values of specific gravity and fineness modulus respectively. Its coefficient of uniformity and coefficient of curvature values of 1.24 and 1.83 respectively, which indicate a poorly graded particle.

3.2 Methods

3.2.1 Determination of properties of Fresh Nanosized Cassava Peel Ash (NCPA)-Concrete

3.2.1.1 Slump Test of NCPA-Concrete

The slump test for concrete was carried out with respect to the standards given in BS EN 12350-2 (2019). The concrete slump-test is an empirical test that evaluates the consistency and compatibility of fresh concrete. The slump cone was filled with the composite in three levels; each layer was stroked 25 times with the aid of 16mm diameter steel rod. When cone was completely filled, the cone was lifted vertically and slump value of concrete mixture was computed using the scale rule.

3.2.1.2 Setting Time Test of NCPA-Concrete

This refers to the time taken for cement paste to harden. This test done was consistent with the outline in BS EN 196-3 (2016) using Vicat apparatus. The Vicat apparatus have the initial and final setting pins for determination of the setting times of the cement-NCPA mortar and that of the control. The initial setting pin was attached to the Vicat apparatus for the determination of the initial setting time of the cement-NCPA mortar and it was calculated as the total duration from when water was initially added to the sample and the time the initial setting needle ceases to penetrate the Vicat mould of 5 mm. After the determination of the initial-setting-time, the initial setting pin was then detached from the apparatus and replaced with the final-setting-pin, which was used to determine the final setting time of the cement-NCPA mortar. The final setting time was calculated as the period from when water was initially added to the sample until the time the final setting pin made an impression on the mould surface.

3.2.2 Determination of Compressive Strengths of NCPA-Concrete at varying Curing Age

A total of nine hundred and eighteen (918) concrete cubes of 150mm x 150mm x 150mm, were made with OPC and NCPA using varied replacement percentage of NCPA at 1.5% intervals (from 0% to 75%). Replicates of three cubes, were cast for each percentage replacement. A mix-ratio of 1:1.5:3 (blended cement: sand: granite) was adopted. Batching was done by weight. Mixing was done manually on a smooth concrete-pavement. The ash was first meticulously mixed with OPC at the required proportion and the homogeneous blend was then mixed with the fine-coarse aggregate mix. Water was gradually included and the whole concrete heap was mixed conscientiously to ensure uniformity.

The uniformed mixture was introduced into metal cubes in different layers and compacted with the tamping rod 25 stroke per layer, finished the top with the trowel and labelled accurately conforming to BS 1881 (1983). The concrete was de-moulded after 24 hours and immersed in a curing tank. They were crushed at 7, 14, 28, 56, 90 and 150 days of curing to obtain their compressive strength.

The mathematical formula was presented as Eqn. 3.1.

$$CS = \frac{\text{Average Failure load (N)}}{\text{cross}-\text{sectional area of concrete cube}(mm^2)} \qquad (3.1)$$

The results obtained from the experimental method were used for ANN model development based on MATLAB computational system. The experimental outcome were compared with the model. The ANN model was validated using statistical student’s T-test.

3.2.3 Development of an Artificial Neural Network (ANN) Model for Anticipating the Compressive Ability of NCPA-concrete.

In engineering, the role of artificial neural network (ANN) in solving diverse problems is of great significance. Complex processes which are fundamentally non-linear systems are mostly handled by models from ANN (Cladera and Mari, 2004). Like a typical human brain, ANN functions much more with elements regarded as neuron. Development of ANN model, requires input and output components, where the latter is totally controlled by the former (Bal, Buyle-bodin, 2013). The neurons are joined together and each link has its own weight (Bilim, Atis, Tanyildizi, Karahan, 2009). The weight multiplied by the transmitted-signals in the network offers the solution to the model. The model consists input factors (X_1, X_2, X_3, X_4---- X_n), having weights (W_1, W_2, W_3, W_4----- W_n), respectively.

The general description of the analogy is given by Eqn. 3.2

$$\text{Output} = \sum_{n=0}^{n} X_n W_n + b \qquad (3.2)$$

Where W_n =weight, and X_n= input, and b = bias.

Basically, the ANN technique comprises of three processes which are training, learning and testing of model performance. ANN model development, was performed using MATLAB software.

3.2.3.1 Architecture of the model

The network consists of the input, hidden and output layer. The input and output layers are fixed before data training, while the hidden layer is ascertained based on trial and error. The input layer consists of six (6) neurons corresponding to the five composite single input water-cement ratio, cement, nanostructured cassava peel ash, sand, granite chippings and curing age. The hidden layer has ten neurons. The target function was the sigmoid-transfer-function. This function helped the network to learn the non-linear relationship between the input data and the output data.

Figure 3.1 shows the architecture within the developed network. It has 6, 10 and 1 as input, hidden layer and output neuron respectively.

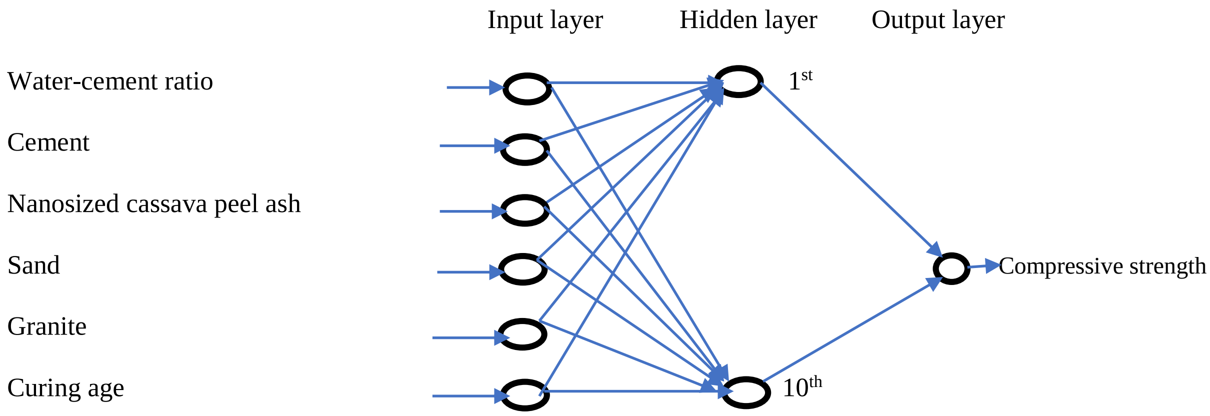

Fig. 3.1. Architecture of the formulated ANN model

The input data were divided into three parts, sixty percent of the data were used at the learning stage, and fifteen percent each for the testing and validation phases, respectively. Training implies supplying sorted datasets with initialized variables and the network being adjusted in accordance with the error function. Validation involves evaluating of the network generalization performance and to stop training when there is no more improvement in the generalization while testing provides the performance during and after training without having any effect on the training phase.

The sum of four hundred (400) data set were introduced to the network. Two hundred and forty (240) of these were used for training, sixty (60) for validation, and another sixty (60) were used for testing. This division was achieved by the use of the 'dividerand' function and the network objects. The Levernberg-Marquardt back-propagation training function (trainlm) was employed as the training function, while the tangent sigmoid function (Tansig) served as the activation function. Data normalization was carried out by default in MATLAB. The process was replicated, based on trial-and-error, before the befitting model was selected.

3.2.3.2. Activation Function

This function permits ANN to execute computations and figure the authentic pointer produced by a neuron. Depending on the type of function adopted, the activation function transforms the solution from the sum function. The activation function concludes whether the neuron gets fired or not. Generally, sigmoid activation function is used for multiple layer feed-forward models (Cladera and Mari, 2004). The output of the neuron is computed using Eqn. (3.3) with a sigmoid activation-function as follows;

$$\text{Output} = \frac{1}{1+e^{-\alpha(sum)}} \tag{3.3}$$

where α is the constant of proportionality used to control the slope of the semi-linear region.

3.2.3.3. Learning of the ANN

This is a critical phase in ANN development, that complements the model performance and better generalization of the data sets as it updates the bias and weights when it is specifically simulated. This process was achieved by modifying the weights with respect to same criterion and comparing the observed upshot and computed outcome of the model to create new and improved values for bias and weights (Chandwani, Agrawal, Nagar, 2013; Awodiji et al., 2018).

3.2.3.4. Back Propagation

This is the process of reducing the weight of neurons that adds to the error while tracking back the neurons of the model, and identifying where the error occurs. The controlled weights enabled back propagation to be used in minimizing the prevised error of the model by simultaneously adjusting the weights.

The mean square error was used for back propagation algorithm and was defined as;

$$E_p = \sum_{k=1}^{p} \frac{1}{2}(t_k - o_k)^2 \tag{3.4}$$

where,

t_k= Target (desired) value of o_k output unit;

o_k= Actual output obtained from o_k output unit

The form of the corresponding error surface was derived by the error-function in combination with the training set. Adopting the Levernberg-Marquardt algorithm, the Eqn 3.4 can be re-written as:

$$E_{p_\beta} = \sum_{k=1}^{p}[t_k - f\left(O_{k,\beta}\right)]^2 \qquad (3.5)$$

where,

t_k= Target (desired) value of O_k output unit.

$f(O_k, \beta)$= Actual output obtained from O_k output unit.

$Ep(\beta)$= Mean square error; β= Parameter vector;

o_k= Measured vector; f= Functional relationship.

The Levenberg-Marqaurdt training algorithm was implemented in the neural network toolbox of Matlab inputting the trainlm function.

3.2.4 Evaluation of the Performance of the ANN model using percentage error method and Student's T-test

3.2.4.1 Percentage Error

The experimental outcome and the ANN model predictions were evaluated using the percentage error method as shown in Eqn 3.6

$$\text{Percentage Error (\%)} = \left(\frac{\text{Experimental Results}}{\text{ANN Prediction}} - 1\right) x\ 100\% \qquad (3.6)$$

3.2.4.2. Student's T-test

The adequacy of the network predictions against the experimental values were tested using the student's t-test as presented in Eqn 3.7

$$T = \frac{D_A\, X\sqrt{N}}{S} \qquad (3.7)$$

Where,

$$D_A = \sum \frac{D_i}{N} \qquad (3.8)$$

$$S = \sqrt{S^2} \qquad (3.9)$$

$$\sum \frac{(D_A - D_i)^2}{(N-1)} \qquad (3.10)$$

Di= E_x-N_p N=Number of responses. Ex= experimental results N_p = Model results

The mix proportions of the constituent materials of concrete are shown in Table 3.1

Table 3.1 Mix Proportion of Constituent Materials for the Concrete Production

Mixture Label	Mix Proportions	Water (kg)	Cement (kg)	NCPA (kg)	Sand (kg)	Granite (kg)
A1	1.000: 0.000: 1.5:3	15.25	25.42	0.00	38.38	76.09
A2	0.985: 0.015: 1.5:3	15.25	25.04	0.38	38.38	76.09
A3	0.970: 0.030: 1.5:3	15.25	24.66	0.76	38.38	76.09
A4	0.955: 0.045: 1.5:3	15.25	24.28	1.14	38.38	76.09
A5	0.940: 0.060: 1.5:3	15.25	23.89	1.53	38.38	76.09
A6	0.925: 0.075: 1.5:3	15.25	23.51	1.91	38.38	76.09
A7	0.910: 0.090: 1.5:3	15.25	23.13	2.29	38.38	76.09
A8	0.895: 0.105: 1.5:3	15.25	22.75	2.67	38.38	76.09
A9	0.880: 0120: 1.5:3	15.25	22.37	3.05	38.38	76.09
A10	0.865: 0.135: 1.5:3	15.25	21.99	3.43	38.38	76.09
A11	0.850: 0.150: 1.5:3	15.25	21.61	3.81	38.38	76.09
A12	0.835: 0.165: 1.5:3	15.25	21.23	4.19	38.38	76.09
A13	0.820: 0.180: 1.5:3	15.25	20.84	4.58	38.38	76.09
A14	0.805: 0.195: 1.5:3	15.25	20.46	4.96	38.38	76.09
A15	0.790: 0.210: 1.5:3	15.25	20.08	5.34	38.38	76.09
A16	0.775: 0.225: 1.5:3	15.25	19.70	5.72	38.38	76.09
A17	0.760: 0.240: 1.5:3	15.25	19.32	6.10	38.38	76.09
A18	0.745: 0.255: 1.5:3	15.25	18.94	6.48	38.38	76.09
A19	0.730: 0.270: 1.5:3	15.25	18.56	6.86	38.38	76.09
A20	0.715: 0.285: 1.5:3	15.25	18.18	7.24	38.38	76.09
A21	0.700: 0.300: 1.5:3	15.25	17.79	7.63	38.38	76.09
A22	0.685: 0.315: 1.5:3	15.25	17.41	8.01	38.38	76.09
A23	0.670: 0.330: 1.5:3	15.25	17.03	8.39	38.38	76.09
A24	0.655: 0.345: 1.5:3	15.25	16.65	8.77	38.38	76.09
A25	0.640: 0.360: 1.5:3	15.25	16.27	9.15	38.38	76.09
A26	0.625: 0.375: 1.5:3	15.25	15.89	9.53	38.38	76.09
A27	0.610: 0.390: 1.5:3	15.25	15.51	9.91	38.38	76.09
A28	0.595: 0.405: 1.5:3	15.25	15.12	10.30	38.38	76.09
A29	0.580: 0.420: 1.5:3	15.25	14.74	10.68	38.38	76.09
A30	0.565: 0.435: 1.5:3	15.25	14.36	11.06	38.38	76.09
A31	0.550: 0.450: 1.5:3	15.25	13.98	11.44	38.38	76.09
A32	0.535: 0.465: 1.5:3	15.25	13.60	11.82	38.38	76.09
A33	0.520:0.480: 1.5:3	15.25	13.22	12.20	38.38	76.09
A34	0.505: 0.495: 1.5:3	15.25	12.84	12.58	38.38	76.09
A35	0.490: 0.510: 1.5:3	15.25	12.46	12.96	38.38	76.09
A36	0.475: 0.525: 1.5:3	15.25	12.07	13.35	38.38	76.09
A37	0.460: 0.540: 1.5:3	15.25	11.69	13.73	38.38	76.09
A38	0.445: 0.555: 1.5:3	15.25	11.31	14.11	38.38	76.09
A39	0.430: 0.570: 1.5:3	15.25	10.93	14.49	38.38	76.09
A40	0.415: 0.585: 1.5:3	15.25	10.55	14.87	38.38	76.09
A41	0.400: 0.600: 1.5:3	15.25	10.17	15.25	38.38	76.09
A42	0.385: 0.615: 1.5:3	15.25	9.79	15.63	38.38	76.09
A43	0.370: 0.630: 1.5:3	15.25	9.41	16.01	38.38	76.09
A44	0.355: 0.645: 1.5:3	15.25	9.02	16.40	38.38	76.09
A45	0.340: 0.660: 1.5:3	15.25	8.64	16.78	38.38	76.09
A46	0.325: 0.675: 1.5:3	15.25	8.26	17.16	38.38	76.09
A47	0.310: 0.690: 1.5:3	15.25	7.88	17.54	38.38	76.09
A48	0.295: 0.705: 1.5:3	15.25	7.50	17.92	38.38	76.09
A49	0.280: 0.720: 1.5:3	15.25	7.12	18.30	38.38	76.09
A50	0.265: 0.735: 1.5:3	15.25	6.74	18.68	38.38	76.09
A51	0.250: 0.750: 1.5:3	15.25	6.36	19.07	38.38	76.09

CHAPTER FOUR

RESULTS AND DISCUSSION

4.1 Results

4.1.1 Presentation of Result for Properties of fresh nanosized cassava peel ash (NCPA)-concrete

4.1.1.1 Presentation of Result of Slump test of NCPA-concrete

The result of slump test for NCPA-Cement concrete mixtures is as shown in Figure 4.1.

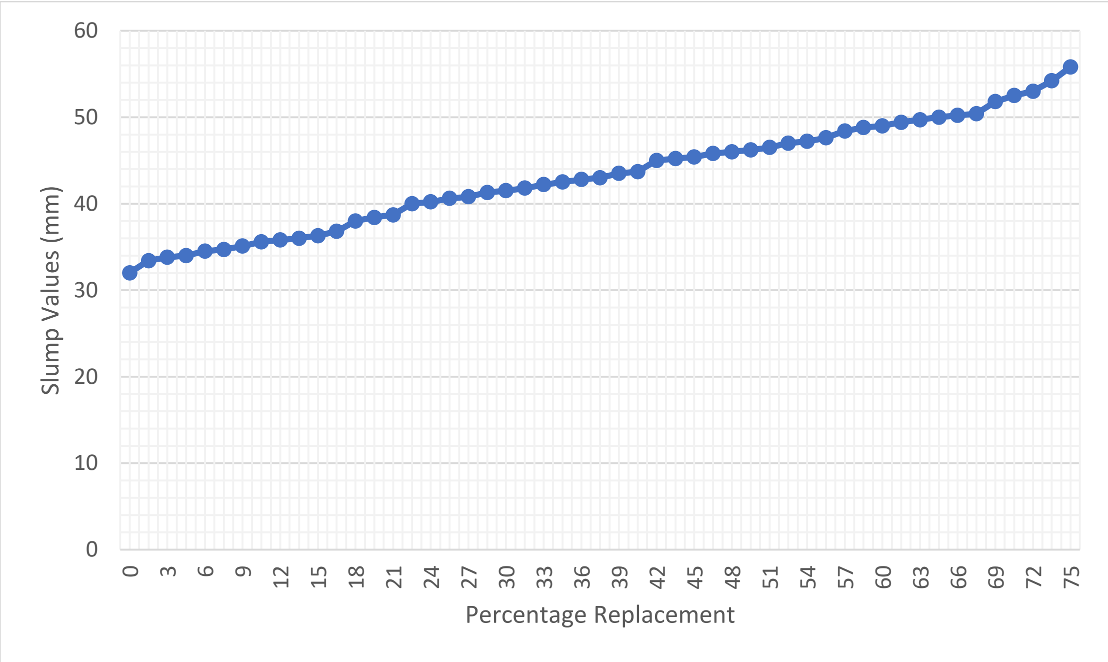

Fig 4.1. Slump of NCPA-Concrete mixes

4.1.1.2 Presentation of Result of Setting time test of NCPA-concrete

The results of setting time test for NCPA-concrete mixtures are as shown in Figure 4.2.

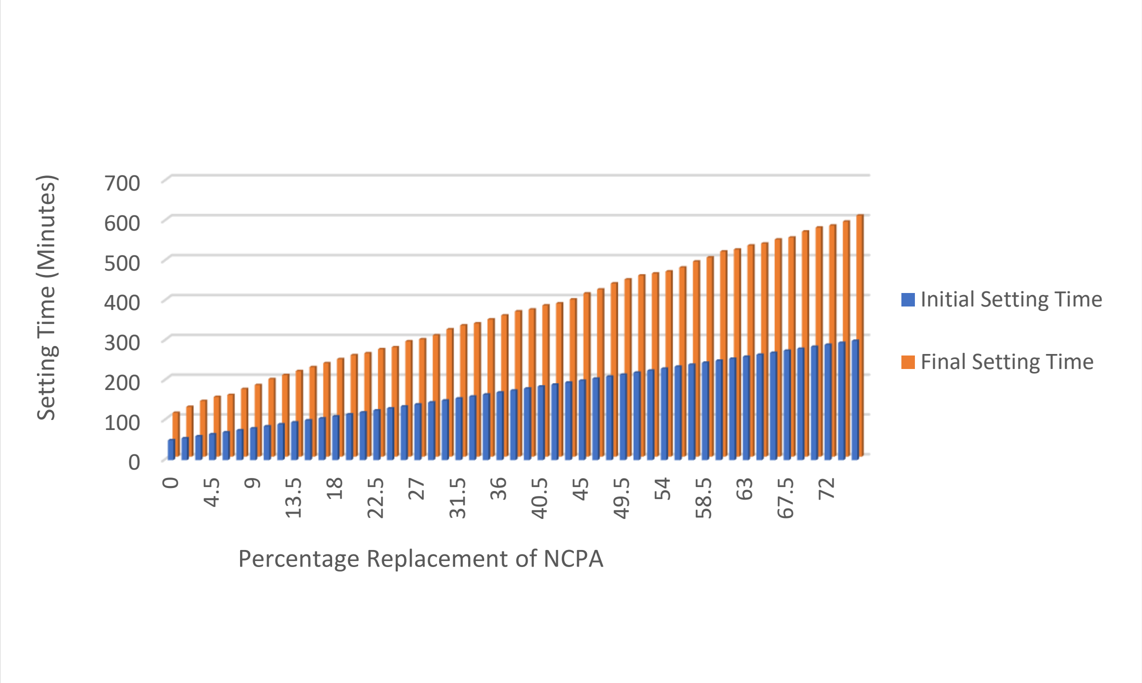

Fig. 4.2: Setting time of NCPA-concrete

4.1.2 Presentation of Result of compressive strength of NCPA-concrete at varying curing ages

The result of compressive strength test on concrete samples is as shown in Figure 4.3

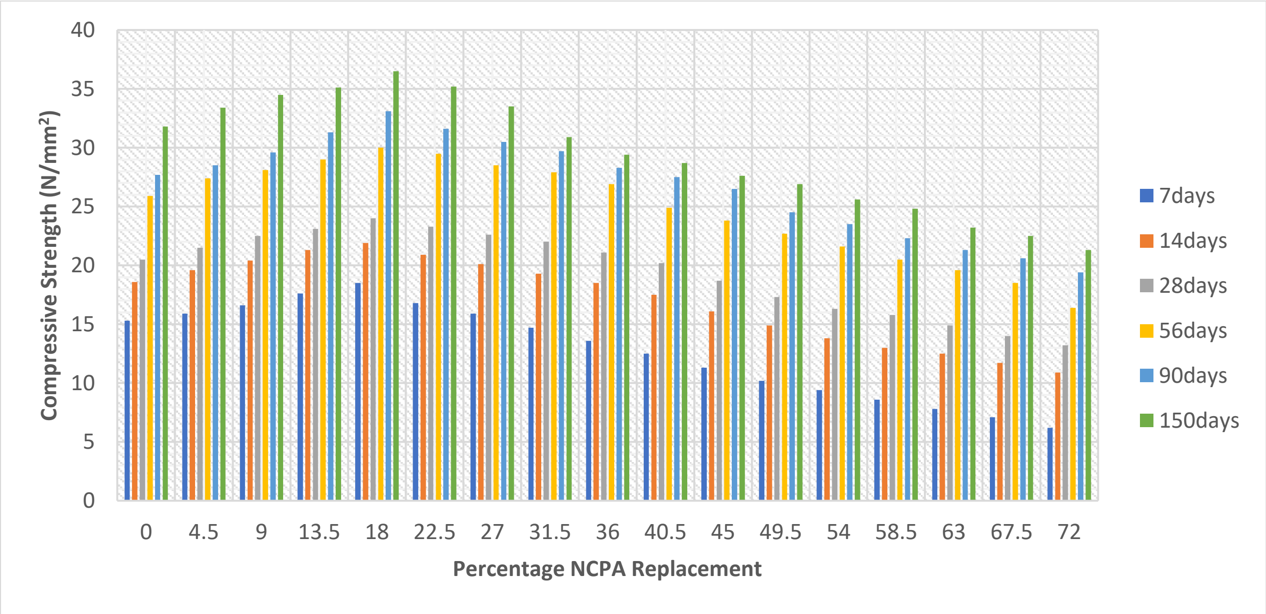

Fig. 4.3 Compressive Strength Variation with Percentage NCPA Replacement at different Curing Periods

4.1.3 Presentation of Result of the artificial neural network (ANN) model for anticipating the compressive ability of the NCPA-concrete.

The result of ANN prediction of compressive strength of the concrete samples is as shown in Plates 4.1, 4.2, 4.3, 4.4 and 4.5.

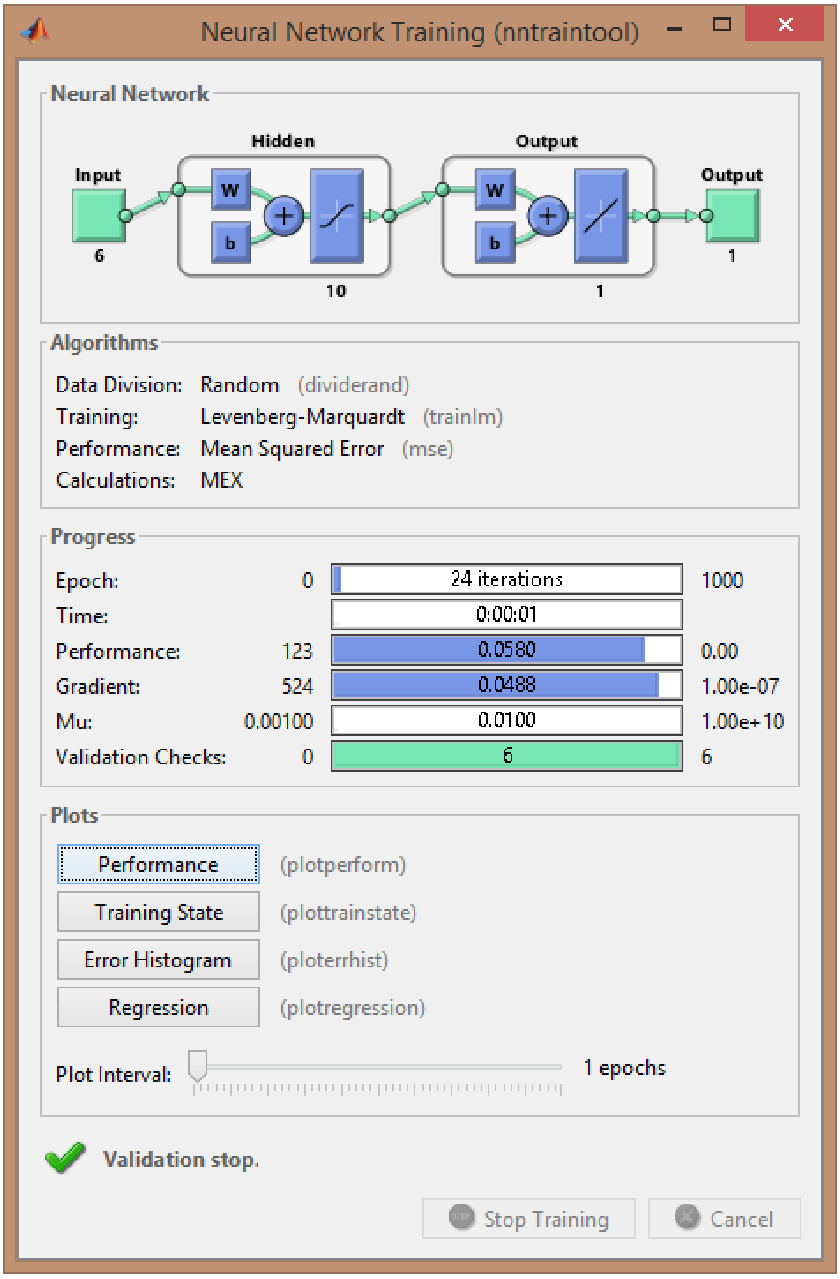

Plate 4.1: The ANN Architecture

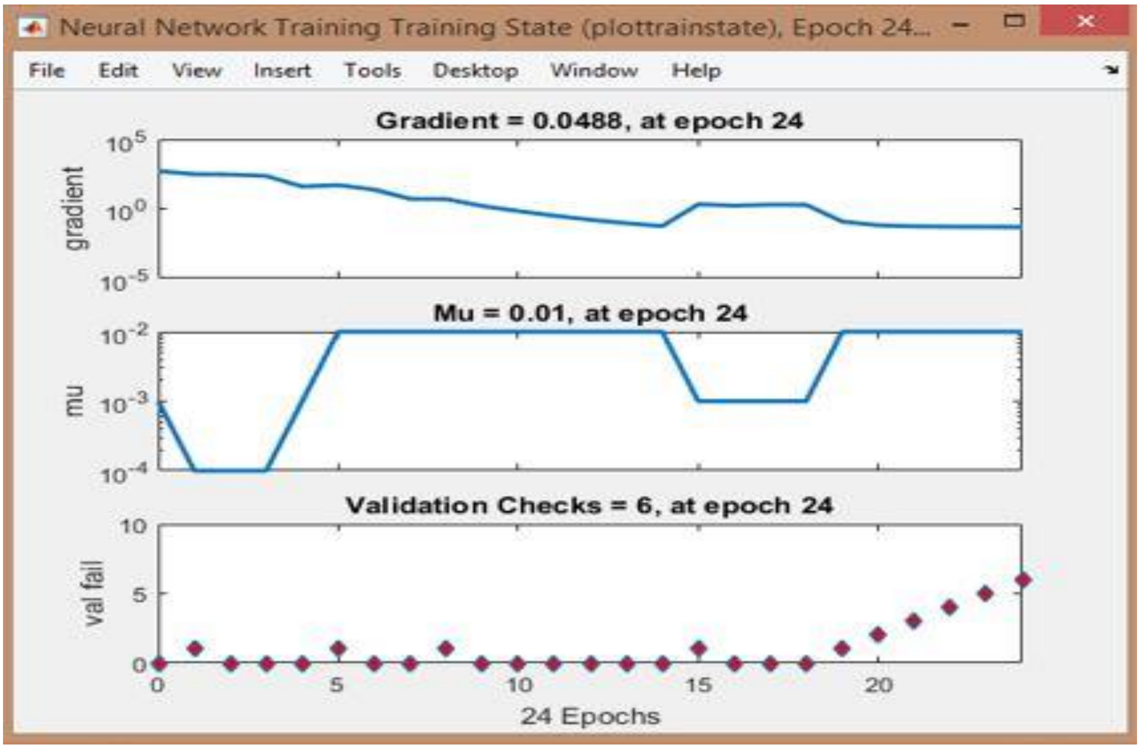

Plate 4.2: ANN training state

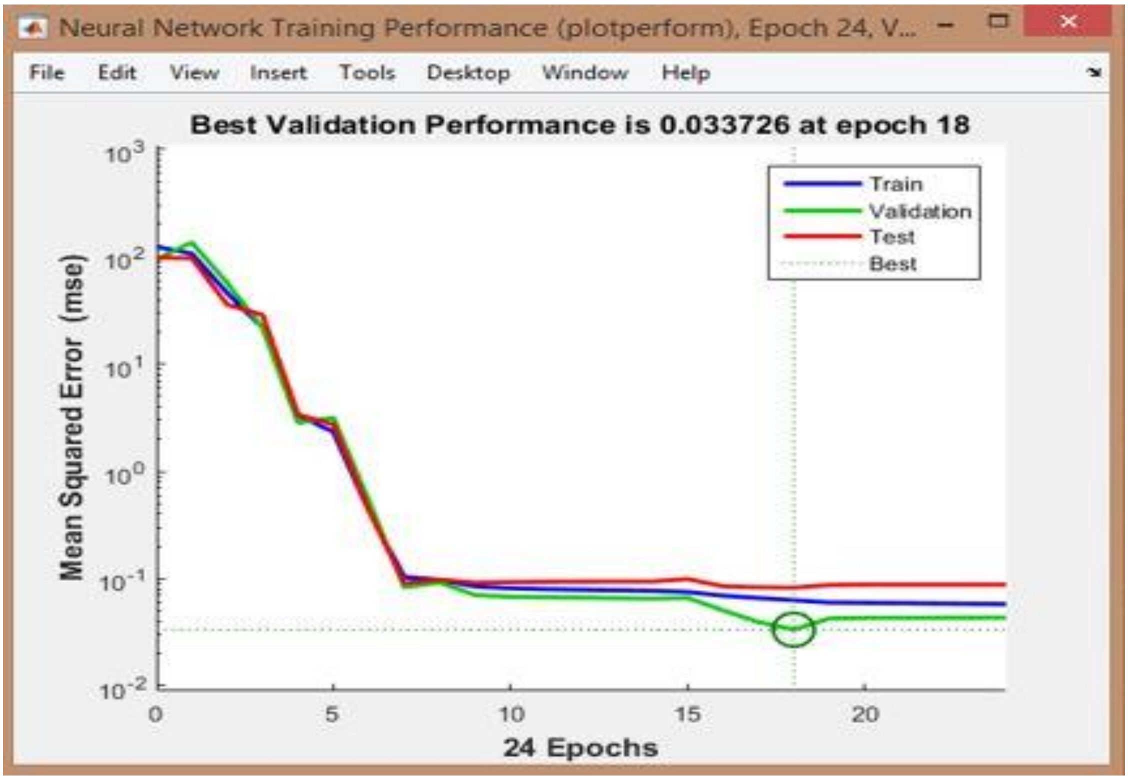

Plate 4.3: Validation performance of the ANN

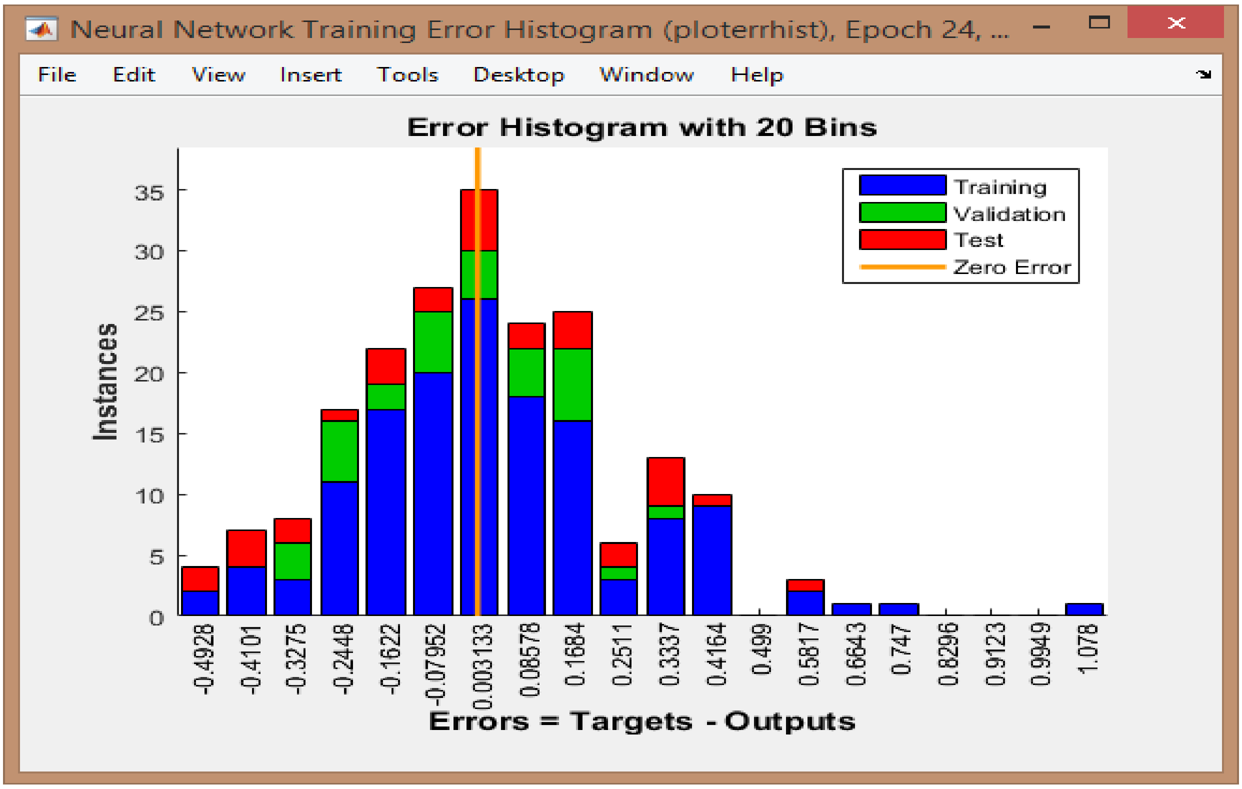

Plate 4.4: ANN error histogram

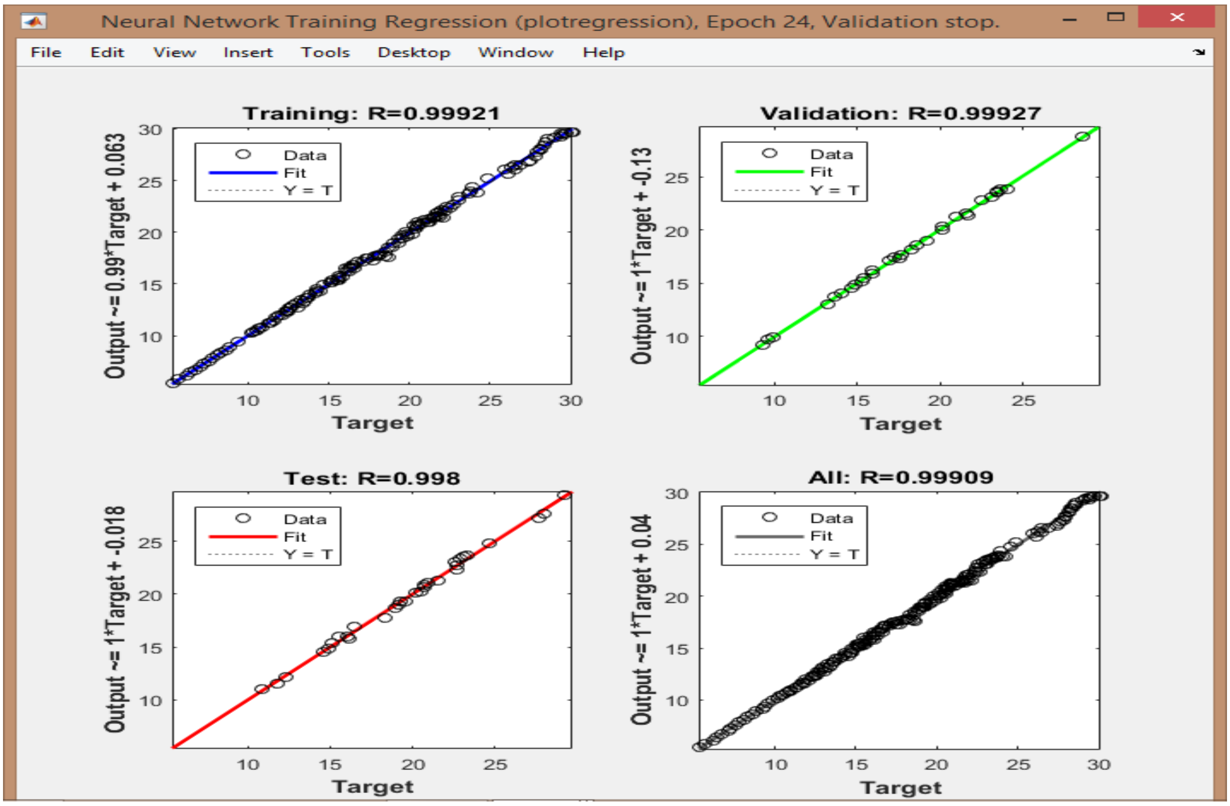

Plate 4.5 Regression plot for training, test and validation of the ANN

4.1.4 Presentation of Validation Results of ANN prediction using the percentage error method and student's T-test

The Table 4.1 shows the comparison of experimental results against ANN prediction of the compressive-strength of concrete incorporating NCPA, using percentage-error approach. These strength values corresponded to concrete specimens B_1, B_2, B_3, B_4, B_5 for the 7 days, 14 days, 28 days, 56 days, 90 days and 150 days' strength at 0%, 3%, 6%, 9% and 12% NCPA replacement respectively.

The Table 4.2 shows the comparison of ANN only against GA-optimized-ANN prediction of the compressive strength of concrete incorporating NCPA using percentage error method.

The upshot of the ANN model was further examined for adequacy using the student's t-test. The Table 4.3 presents the results obtained from this test.

Table 4.1 Comparison of Experimental Results against Neural Network Prediction for the Compressive Strength of NCPA Concrete using Percentage Error Method.

Mix Label	Curing Age	Experimental Results (N/mm^2)	ANN Prediction (N/mm^2)	Error	% Error
B_1	7	15.30	15.339	-0.039	-0.25425
B_2	7	15.60	16.210	-0.61	-3.76311
B_3	7	16.10	16.320	-0.22	-1.34804
B_4	7	16.60	17.021	-0.421	-2.47342
B_5	7	17.40	17.424	-0.024	-0.13774
B_1	14	18.60	18.642	-0.042	-0.2253
B_2	14	19.20	19.457	-0.257	-1.32086
B_3	14	19.90	19.834	0.066	0.332762
B_4	14	20.40	20.423	-0.023	-0.11262
B_5	14	20.90	20.776	0.124	0.596843
B_1	28	20.50	21.235	-0.735	-3.46127
B_2	28	21.20	21.845	-0.645	-2.95262
B_3	28	21.80	21.569	0.231	1.070982
B_4	28	22.50	22.522	-0.022	-0.09768
B_5	28	23.00	23.234	-0.234	-1.00714
B_1	56	25.90	24.171	1.729	7.1532
B_2	56	26.50	26.435	0.065	0.245886
B_3	56	27.60	27.578	0.022	0.079774
B_4	56	28.10	27.835	0.265	0.952039
B_5	56	28.60	28.722	-0.122	-0.42476
B_1	90	27.70	27.345	0.355	1.298226
B_2	90	28.30	28.240	0.06	0.212465
B_3	90	28.90	28.458	0.442	1.553166
B_4	90	29.60	29.456	0.144	0.488865
B_5	90	31.00	31.456	-0.456	-1.44964
B_1	150	31.80	32.324	-0.524	-1.62109
B_2	150	32.80	32.671	0.129	0.394846
B_3	150	33.70	33.586	0.114	0.339427
B_4	150	34.50	34.236	0.264	0.771118
B_5	150	35.00	34.898	0.102	0.29228

Table 4.2 Comparison of ANN only against GA-optimized-ANN Prediction for the Compressive Strength of NCPA Concrete using Percentage Error Method.

Mix Label	Curing Age	ANN Prediction (N/mm^2)	GA-optimized ANN prediction (N/mm^2)	Error	% Error
B_1	7	15.339	16.164	-0.825	-5.10393
B_2	7	16.210	17.342	-1.132	-6.52751
B_3	7	16.320	15.867	0.453	2.854982
B_4	7	17.021	18.678	-1.657	-8.8714
B_5	7	17.424	18.320	-0.896	-4.89083
B_1	14	18.642	18.189	0.453	2.490516
B_2	14	19.457	21.239	-1.782	-8.39023
B_3	14	19.834	18.038	1.796	9.956758
B_4	14	20.423	21.324	-0.901	-4.22529
B_5	14	20.776	21.290	-0.514	-2.41428
B_1	28	21.235	21.456	-0.221	-1.03001
B_2	28	21.845	23.189	-1.344	-5.79585
B_3	28	21.569	22.756	-1.187	-5.21621
B_4	28	22.522	22.345	0.177	0.792124
B_5	28	23.234	24.345	-1.111	-4.56357
B_1	56	24.171	23.870	0.301	1.260997
B_2	56	26.435	25.210	1.225	4.859183
B_3	56	27.578	28.457	-0.879	-3.08887
B_4	56	27.835	29.345	-1.51	-5.14568
B_5	56	28.722	29.745	-1.023	-3.43923
B_1	90	27.345	28.289	-0.944	-3.33699
B_2	90	28.240	29.456	-1.216	-4.12819
B_3	90	28.458	26.980	1.478	5.478132
B_4	90	29.456	28.685	0.771	2.687816
B_5	90	31.456	32.370	-0.914	-2.8236
B_1	150	32.324	33.135	-0.811	-2.44756
B_2	150	32.671	33.760	-1.089	-3.22571
B_3	150	33.586	34.315	-0.729	-2.12444
B_4	150	34.236	36.210	-1.974	-5.45153
B_5	150	34.898	36.364	-1.466	-4.03146

Table 4.3. Statistical student's T-test for ANN model validation

S/No.	E_x	N_p	$D_i=E_x-N_p$	$D_A=(\sum D_i)/N$	D_A-D_i	$(D_A-D_i)^2$
1	15.30	15.339	-0.039	-0.008733	0.030267	0.000916
2	15.60	16.210	-0.61	-0.008733	0.601267	0.361522
3	16.10	16.320	-0.22	-0.008733	0.211267	0.044634
4	16.60	17.021	-0.421	-0.008733	0.412267	0.169964
5	17.40	17.424	-0.024	-0.008733	0.015267	0.000233
6	18.60	18.642	-0.042	-0.008733	0.033267	0.001107
7	19.20	19.457	-0.257	-0.008733	0.248267	0.061637
8	19.90	19.834	0.066	-0.008733	-0.07473	0.005585
9	20.40	20.423	-0.023	-0.008733	0.014267	0.000204
10	20.90	20.776	0.124	-0.008733	-0.13273	0.017618
11	20.50	21.235	-0.735	-0.008733	0.726267	0.527464
12	21.20	21.845	-0.645	-0.008733	0.636267	0.404836
13	21.80	21.569	0.231	-0.008733	-0.23973	0.057472
14	22.50	22.522	-0.022	-0.008733	0.013267	0.000176
15	23.00	23.234	-0.234	-0.008733	0.225267	0.050745
16	25.90	24.171	1.729	-0.008733	-1.73773	3.019716
17	26.50	26.435	0.065	-0.008733	-0.07373	0.005437
18	27.60	27.578	0.022	-0.008733	-0.03073	0.000945
19	28.10	27.835	0.265	-0.008733	-0.27373	0.07493
20	28.60	28.722	-0.122	-0.008733	0.113267	0.012829
21	27.70	27.345	0.355	-0.008733	-0.36373	0.132302
22	28.30	28.240	0.06	-0.008733	-0.06873	0.004724
23	28.90	28.458	0.442	-0.008733	-0.45073	0.20316
24	29.60	29.456	0.144	-0.008733	-0.15273	0.023327
25	31.00	31.456	-0.456	-0.008733	0.447267	0.200048
26	31.80	32.324	-0.524	-0.008733	0.515267	0.2655
27	32.80	32.671	0.129	-0.008733	-0.13773	0.01897
28	33.70	33.586	0.114	-0.008733	-0.12273	0.015063
29	34.50	34.236	0.264	-0.008733	-0.27273	0.074383
30	35.00	34.898	0.102	-0.008733	-0.11073	0.012262

Where;

E_x = Experimental responses.

N_p=Neural network model responses.

N = the Number of Responses = 30.

$\sum D_i$= -0.262

$\sum (D_A - D_i)^2 = 5.768$

$S^2 = [\sum(D_A - D_i)^2]/(N-1) = 0.199$

$S = \sqrt{S^2} = 0.446$

$D_A \times \sqrt{N} = -0.0478$

$T = [D_A \times \sqrt{N}]/S = -0.107$

Degree of freedom = N-1

5% significance for a two-tailed test = 0.05

From standard statistical table, $T = T_{(0.05,\, n-1)} = T_{(0.05,29)} = 2.04$

4.2 Discussion of Results

4.2.1 Discussion of Result for properties of fresh NCPA-concrete

4.2.1.1 Discussion of Result of Slump test of NCPA-concrete

The slumps of NCPA-cement mixes at different replacement levels were shown in Figure 4.1. The values obtained from the slump test correspond to the designed slump range of 30 - 60mm. It was observed from Figure 4.1, that the workability increased with expanded replacement. This outcome was consistent with that of Le and Ludwig (2016). The improved workability is attributed to the filler-effect of NCPA between aggregates and cement particles which reduces friction between particles and provides a better concrete-flow.

The nanosization concept increased the fineness of the pozzolanic material (NCPA) and this led to increased workability; hence cohesion was increased and bleeding reduced. In line with Abram's law of water-cement ratio (Kamau et al., 2016), the possibility of optimizing strength using less water in NCPA-concrete was highlighted. Due to the improved workability, easier placing and compaction was achieved.

4.2.1.2 Discussion of Result of Setting time test of NCPA-concrete

It is observed from Figure 4.2, that the initial and final setting-times increased as the NCPA replacement percentage increased, thereby retarding the hydration process. This implied that NCPA concrete is not susceptible to the problem of false set. This was due to decrease in the strength-forming compounds (C_3S, C_2S, and C_3A) in the cement-paste. The results obtained satisfied the prescriptions of ASTM C 150 (1994).

4.2.2 Discussion of Result of compressive strength of NCPA concrete at varying curing ages

The Figure 4.3 summarized the results obtained. The result showed that the compressive strength increased as the percentage replacement of the cement with NCPA increased and as the curing age increased. From the figure, it was observed that inclusion of NCPA in concrete mix was very effective in increasing the compressive strength of concrete. This could be ascribed to oxides of silica and alumina (SiO_2 and Al_2O_3) of NCPA content being larger than those of OPC as indicated in Table 3.1. The increasing strength is also traceable to the formation of strengthening gel (C-S-H) and bond (C-A-H) occurring from the reaction of NCPA's silica and alumina elements with the hydrating agents of OPC (Khan, Nuruddin, Ayub and Shafiq, 2014). It can be seen that the compressive strength increased up to 19.5% replacement of cement with nano cassava peel ash. There is a clear difference between this study and the previous studies on cassava peel ash that was not nano-sized. The outcome of this study, is in agreement with the works performed by (Wani and Rahman, 2017; Milton and Gnamaraji, 2020).

The addition of NCPA to the concrete gave a unique surface area-to-volume ratio and filled the pores existing in the matrix which in turn enhanced concrete strength. The maximum compressive strength of 36.90 N/mm^2 was achieved at 19.5% replacement at 150 days of age.

4.2.3 Discussion of Result of the ANN model for anticipating the compressive ability of the NCPA concrete

The Plates 4.1, 4.2, 4.3, 4.4, and 4.5 are results obtained from MATLAB software. The network architecture as shown in Chapter 3, is 6-10-1 with OPC, NCPA, water, sand, granite, and water-cement ratio as the input parameter while the output parameter is the concrete compressive strength for curing days of 7, 14, 28, 56, 90 and 150, respectively. The generalization of the data set helped to evaluate the behaviour of concrete with NCPA replacements.

4.2.3.1 ANN training state

The status-progress bar through the network training processes, is captured in this state. The plotted graph indicates the gradient plot, last epoch (Mu) and validation checks against Epoch. Epoch refers to training the model using the entire training data for one-cycle.

After executing 6 validation inspection before merging as shown in Plate 4.2, a gradient of 0.0488 aiming $1.0e^{-07}$ was attained at this point. It was detected that the best validation checks materialized at the 18^{th} epoch and a mean-square-error of 10^{-2}, and best operation was at 0.0337. The gradient at the very last epoch (Mu) was 0.01. The Plate 4. 2 presented the training state of the model; the errors are duplicated sometime after epoch 18 and at epoch 24, the test was terminated. The epoch 18 was selected as the base and its weights were chosen as the final weights.

4.2.3.2 ANN validation performance

The behaviour of the network during training was plotted against the number of epochs. The Plate 4.3 shows the mean squared error and validation performance of the model beginning from big values and dropping to a small value. The training, validation, and test were indicated in the graph. It was observed that the optimal validation check happened at the 18^{th} epoch with best performance of 0.033726 and the process was concluded at epoch 24 as seen in the x-axis of the plot.

4.2.3.3 ANN error histogram

The chart illustrates the lapses between the predicted and existing values after ANN training. Errors show the contrast between the anticipated and the actual experimental values. The error histogram is presented in plate 4.4 with 20 bins for the validation, test and training, in ANN modelling. The diagram depicts that the 14th bin has zero-error at 0.003133 and generated the best operation for the model. The zero-error was shown with a yellow line at the center with 25 instances in the training set.

4.2.3.4 ANN regression plot

The relationship between the target and response variables being the determination coefficient for validation, training and testing measures were shown in plate 4.5 respectively. Three plots which represent training, validation and testing datasets were presented while the dashed line in the plots, represent the regression line at zero error. The closeness of the data sets to the fitted regression line is captured with R-values. The target values shown in the graph implied that they are measured-values and the output values are the predicted-values.

The R-value encapsulates the relation between the outputs and targets. If $R = 1$, then there is a linear correlation between the output and the targets (Awodiji *et al.,* 2018). The statistical computation results obtained, showed adequate performance in terms of prediction-accuracy of the model with 0.9992, 0.9980, 0.9993 values obtained for training, testing, validation respectively and finally 0.9991 for all. These values are very close to 1, showing that the model has good predicting ability.

4.2.4 Discussion of Result of Validation the network prediction using the percentage error method and student's T-test.

Considerable encouraging results have been provided by the model utilizing the experimental data. In Table 4.1, the greatest percentage-error obtained was 7.15%, which was not up to 10%. This result further confirms that the model has been sufficiently trained, as all outputs given by the network, are just-about the values obtained from the experiment. A two-tailed student's T- test was done and the computations presented in Table 4.3. The computed T-value from of the model is -0.11 which is less than the standard T-value of 2.04 obtained from the standard statistical tables given in appendix C. The adequacy test confirms that the result from model are reliable and could be used to predict the 7^{th}, 14^{th}, 28^{th}, 56^{th}, 90^{th} and 150^{th} day compressive strength of NCPA-concrete at 95% confidence level.

CHAPTER FIVE

CONCLUSION AND RECOMMENDATION

5.1 Conclusion

In this study, the slump value increased as the NCPA percentage replacement increased. Ease of placement and compaction was enhanced due to the filler effect of NCPA between the binder and the aggregates. The initial and final setting-time of the OPC-NCPA mixes was found to rise with increasing replacement. This shows that the concrete is not susceptible to premature stiffening.

The compressive strength of NCPA-concrete increased as the curing age increased for each of the NCPA percentage replacement. Beyond 20%, the strength declined as the CPA content increased. 19.5% and water-cement ratio of 0.75 are considered as the optimum dose to achieve grade 30 NCPA concrete. 36.90 N/mm^2 was obtained as optimum strength at 150 curing days.

The ANN modelled strength were equivalent to those of the laboratory tests. The smallest and highest correlation-coefficients recorded for all data samples employed for the model, were 0.9980 and 0.9992 for the test and training specimen respectively. These values were close to 1, which indicates that the developed ANN-model has a satisfactory and outstanding predicting ability.

The suitability of the model was evaluated using the student’s T-test. The T-value of the computed strength of NCPA-concrete, was lower than that from the standard T-table at 95% confidence level, showing that the network predictions are reliable.

5.2 Contributions to Knowledge

This study contributed the following to knowledge;

i. It proved that nanosization of supplementary cementitious materials improves concrete strength.
ii. It deduced that the substitution of cement with NCPA must not exceed 20%, if NCPA-concrete is to be used as a structural material.
iii. It showed that optimum strength for NCPA-concrete can be achieved at a water-cement ratio of 0.75 at 19.5% replacement for 7, 14, 28, 56, 90 and 150 days of curing.
iv. It proved that ANN model is reliable and worthy of adoption for strength prediction when it's adequacy was examined with student's test and percentage error approach.

5.3 Recommendations

Based on the outcome of this study, the following recommendations are made;

i. The ANN model developed herein is apt for optimization of compressive strength of NCPA-concrete.
ii. Extra studies should be carried be out on the espousal of nanosization of other supplementary cementitious materials such as rice husk ash, bambara nut shell ash, oyster shell ash, sugarcane-bagasse ash and sawdust ash.
iii. Further investigations should be carried out on the application of ANN to predict other attributes of NCPA-cement concrete, such as modulus of rupture, elastic modulus, flexural strength and shear modulus.
iv. Extensive research should be carried out on the use of other soft computing techniques such as fuzzy-logic and adaptive network based fuzzy-inference system, to predict various properties of NCPA-concrete.

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APPENDICES

APPENDIX A: Specific gravity of Concrete constituents

Table 1: Chemical Composition of BUA cement and Nanosized Cassava Peel Ash (NCPA)

Materials	Chemical Composition (%)								
	SiO_2	Fe_2O_3	Al_2O_3	CaO	SO_3	MgO	Na_2O	K_2O	LOI
BUA Cement	18.22	2.72	5.11	60.14	3.31	1.25	0	0.08	7.23
NCPA	61.70	2.52	12.50	9.42	2.10	6.32	0.05	6.82	5.07

Table 2: Results of the Specific Gravity of Fine Aggregates

Specific gravity of fine aggregates		
Description	**Test 1**	**Test 2**
Weight of Empty Bottle (g) A	147.25	150.16
Weight of Bottle + Sample (g) B	740.33	538.60
Weight of Bottle + Sample +Water (g) C	1042.95	916.78
Weight of Bottle + Water (g) D	674.39	674.39
Weight of Sample (g) E=(B-A)	593.08	388.44
Weight of Water in Full Bottle F=(D-A)	527.14	524.23
Weight of Water Used (g) G=(C-B)	302.62	378.18
Volume of Particles (Cm^3) H=(F-G)	224.52	146.05
Specific Gravity I= (E/H)	2.64	2.66
Average Specific Gravity ($I_1+I_2/2$)	**2.65**	

Table 3: Results of the Specific Gravity of Coarse Aggregates

Specific gravity of coarse aggregates		
Description	**Test 1**	**Test 2**
Weight of Empty Bottle (g) A	1030.12	1030.58
Weight of Bottle + Sample (g) B	2495.57	2334.81
Weight of Bottle + Sample +Water (g) C	3204.93	3104.05
Weight of Bottle + Water (g) D	2293.00	2293.00
Weight of Sample (g) E=(B-A)	1465.45	1304.23
Weight of Water in Full Bottle F=(D-A)	1262.88	1262.42
Weight of Water Used (g) G=(C-B)	709.36	769.24
Volume of Particles (Cm^3) H=(F-G)	553.52	493.18
Specific Gravity I= (E/H)	2.65	2.64
Average Specific Gravity ($I_1+I_2/2$)	**2.65**	

APPENDIX A: Specific gravity of Concrete constituents (Continued)

Table 4: Results of the Specific Gravity of Cement

Specific Gravity of BUA Cement		
Description	**Test 1**	**Test 2**
Weight of Empty Bottle M_1 (g)	28.50	28.10
Weight of Bottle + Cement M_2 (g)	50.40	50.00
Weight of Bottle + Cement +Kerosene M_3 (g)	85.10	85.90
Weight of Bottle + Kerosene M_4(g)	68.80	68.30
Weight of Bottle + Water M_5(g)	77.80	78.80
Specific Gravity $= \frac{M_2-M_1}{(M_3-M_1)-(M_5-M_1)}$	3.00	3.08
Average Specific Gravity	**3.04**	

Table 5: Specific Gravity of NCPA

Specific Gravity of NCPA		
Description	**Test 1**	**Test 2**
Weight of Empty Bottle (g)	145.44	146.72
Weight of Bottle + Sample (g)	529.57	494.07
Weight of Bottle + Sample +Kerosene (g)	803.54	788.11
Weight of Bottle + Kerosene (g)	569.91	569.91
Weight of Bottle + Water (g)	671.49	671.49
Specific Gravity	2.05	2.17
Average Specific Gravity	**2.11**	

APPENDIX B: Sieve Analysis of Concrete Constituents

Table 1: Results of Sieve Analysis of Sand

Mass of Dry Sample =948.71g						
Sieve Size / Sieve opening	Mass of Weighting Sieve	Mass of Sieve + Soil Retained	Mass of Sample Retained on each Sieve	Percentage Retained on each Sieve	Cumulative Percentage Retained	Percentage Passing
(mm)	(g)	(g)	(g)	(%)	(%)	(%)
4.75	352.71	358.21	5.50	0.58	0.58	99.42
2	377.28	410.09	32.81	3.46	4.04	95.96
1.18	366.13	434.77	68.64	7.24	11.27	88.73
0.6	360.29	643.07	282.78	29.81	41.08	58.92
0.425	347.03	496.02	148.99	15.70	56.78	43.22
0.3	344.02	614.56	270.54	28.52	85.30	14.70
0.15	340.13	409.20	69.07	7.28	92.58	7.42
0.075	337.63	389.36	51.73	5.45	98.03	1.97
Pan	301.79	318.03	16.24	1.71	99.75	0.25
Total			946.30	99.75		

Table 1b: Results of Sieve Analysis Calculations on Sand

% Loss During Analysis= 0.254		Weight Check	Percentage	
D_{10} = 0.23	Cc $=(D_{30})^2/(D_{10} \times D_{60})$ = 0.960	Weight of Coarse Fraction	0.58	Maximum Aggregate Size (Identified) (mm)= 5
D_{30} = 0.37	Cu $=D_{60}/D_{10}$ = 2.696	Weight of Sand Fraction	97.45	Av. Percentage Passing 4.75mm Sieve (%) = 99.17
D_{40} = 0.41	FM = (Sum of Cumulative Percent Retained)/100 =**2.916**	Weight of Fine	1.71	Av. Percentage Passing 75µm Sieve (%) = 1.71
D_{60} = 0.62		Weight of Materials Accounted for (g)	99.75	

Where:

D_{10} = Particle size at 10%
D_{30} = Particle size at 30%
D_{40} = Particle size at 40%
D_{60} = Particle size at 60%
C_C =Coefficient of curvature
C_U = Coefficient of uniformity
FM = Fineness Modulus

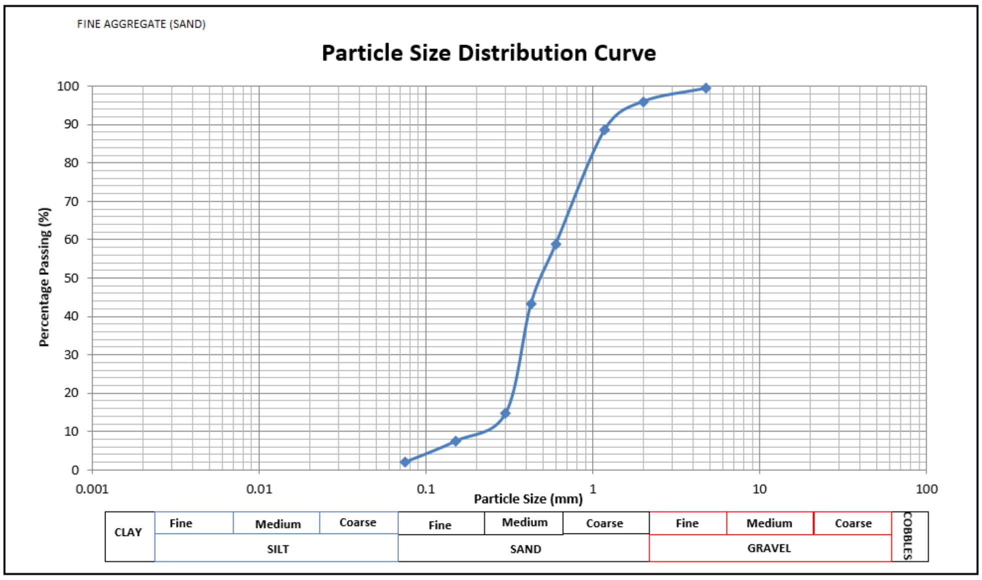

Fig. 1: Sieve Analysis of Fine Aggregate

APPENDIX B: Sieve Analysis of Concrete Constituents (Continued)

Table 2: Results of Sieve Analysis of Coarse Aggregates

Mass of Dry Sample = 3217.28g						
Sieve Size / Sieve opening	Mass of Weighting Sieve	Mass of Sieve + Soil Retained	Mass of Sample Retained on each Sieve	Percentage Retained on each Sieve	Cumulative percentage Retained;	Percentage Passing;
(mm)	(g)	(g)	(g)	(%)	(%)	(%)
31.5	721.72	721.72	0.00	0.00	0.00	100.00
22.4	720.82	802.04	81.22	2.52	2.52	97.48
19	774.42	1217.37	442.95	13.77	16.29	83.71
16	746.80	1740.16	993.36	30.88	47.17	52.83
12.5	766.03	1660.18	894.15	27.79	74.96	25.04
9.5	676.70	1126.21	449.51	13.97	88.93	11.07
6.3	705.36	1002.16	296.80	9.23	98.16	1.84
4.75	683.94	726.61	42.67	1.33	99.48	0.52
Pan	716.76	731.50	14.74	0.46	99.94	0.06
Total			3215.40	99.94		

Table 2b: Results of Sieve Analysis Calculations for Granite

% Loss During Analysis= 0.058		Weight Check	Percentage	
D_{10} = 9.3	Cc =$(D_{30})^2$/ (D_{10} X D_{60}) = 1.240	Weight of Coarse Fraction	0.00	Maximum Aggregate Size (Identified) (mm) = 26
D_{30} = 14	Cu =D_{60}/D_{10} 1.828	Weight of Sand Fraction	99.48	Av. Percentage Passing 4.75mm Sieve(%) = 99.94
D_{40} = 16	FM = (Sum of Cumulative Percent Retained)/100 =**3. 281**	Weight of Fine	0.46	Av. Percentage Passing 75μm Sieve(%) = 0.46
D_{60} = 17		Weight of Materials Accounted for (g)	99.94	

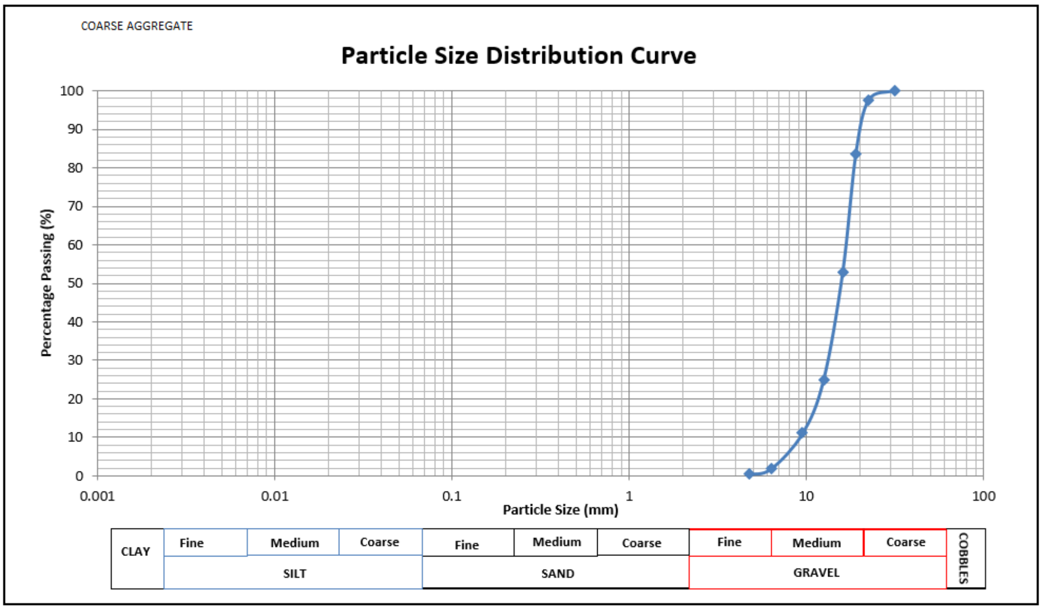

Fig. 2: Sieve Analysis of Coarse Aggregate

APPENDIX C: Concrete Mix Design

Parameters

Characteristic strength	= 30 N/mm^2 at 28days
Standard deviation	= 6.0 N/mm^2
Assumed defective	= 5%
For 5% defective level specified in BS 5328, K	=1.64
Cement type	= OPC (BUA brand)
Slump	= 30 – 60 mm
Proportion of fine aggregate	= 24%
Free water-cement ratio	= 0.60
Free water content	= 180 kg/m^3
Maximum aggregate size	= 20 mm
Minimum cement content	= 290 kg/m^3
Grading of fine aggregate	= Zone 3
Relative density of aggregate	= 2.6
Concrete density	= 2365 kg/m^3
Aggregate type	= Coarse and fine aggregate (Uncrushed)

Calculations

Margin = k. s = 1.64 x 6 = 9.84 N/mm^2

Target mean strength $F_m = F_c + 1.64s = 30 + 9.84 = 39.84$ N/mm^2

$$Cement\ Content = \frac{Free - water\ content}{Free - water\ cement\ ratio} = \frac{180}{0.60} = 300\ kg/m^3$$

Total aggregate content = Wet density – cement content – free water content

= 2365 – 300 – 180

= 1885 kg/m^3

Proportion of fine aggregate = 24 %

Fine aggregate content = 0.24 x 1885 = 452.4 kg/m^3

Coarse aggregate content = 1885 – 452.4 = 1032.6 kg/m^3

Volume of 150mm x 150mm x 150mm concrete cube = 0.15 x 015 x 0.15 m^3

Pre-trial mix = volume x quantity

APPENDIX C: Concrete Mix Design (Continued)

Mix Design Conclusion

Quantity	**Water content (kg/m^3)**	**Cement content (kg/m^3)**	**Fine Aggregate (kg/m^3)**	**Coarse Aggregate (kg/m^3)**
	180	300	452.4	1032.6
Volume of Cube = 0. 003375		300 x 0.00375 = 1.01	452.4 x 0.003375 =1.53	1032.6 x 0.003375 =3.49
Pre-trial Mix		1.01/1.01	1.53/1.01	3.49/1.01
Ratio		1	1.51	3.46
Concrete Mix ratio = 1: 1.5: 3				

APPENDIX D: Calculation for batching

Parameters

Volume of mould = $0.15m \times 0.15m \times 0.15m = 3.375\times10^{-3}m^3$

Area of mould =0.15m x 0.15m = $0.0225m^2$

Specific gravity of Fine Aggregate =2.65

Specific gravity of Coarse Aggregate =2.65

Specific gravity of Cement =3.04

Specific gravity of Water =1.0

Mix ratio = 1: 1.5: 3 (see Mix design and Table 2.4 in clause 2.6.1)

Water Cement ratio = 0.6 (clause 6.1.2, 8.2.4.1 and 9.1.2 of IS 10262 (2009) Code Chart)

Calculation of the weight of materials for one cube sample of the control

Weight ratio = $Water$: $Cement$: $Fine\ Agg$: $Coarse\ Agg$

Weight ratio =0.6: 1: 1.5: 3

Volume ratio =$\frac{0.6}{1} : \frac{1}{3.04} : \frac{1.5}{2.65} : \frac{3}{2.65}$

Volume ratio = 0.60: 0.33: 0.57 :1.13

Total volume ratio = 2.63

Volume of water = $\frac{0.6\ X\ 3.375\ X10^{-3}}{2.63} = 7.6996\ X\ 10^{-3}m^3$

Volume of cement = $\frac{0.33\ X3.375\ X10^{-3}}{2.63} = 4.2348\ X\ 10^{-4}m^3$

Volume of fine aggregate = $\frac{0.57\ X\ 3.375\ X10^{-3}}{2.63} = 7.3146\ X\ 10^{-4}m^3$

Volume of coarse aggregate =$\frac{1.13\ X\ 3.375\ X10^{-3}}{2.63} = 1.4501\ X\ 10^{-3}m^3$

Weight of water = 7.6996 x 10^{-4} x 1.0 x 1000 =0.76996kg

Weight of cement = 4.2348 x 10^{-4} x 3.04 x 1000 =1.28738kg

Weight of fine aggregate = 7.3146 x 10^{-4} x 2.65 x 1000 =1.93837kg

Weight of coarse aggregate = 1.4501 x 10^{-3} x 2.65 x 1000 =3.84277kg

<u>Adding 10% waste to weight of constituents</u>.

Weight of water =0.84696kg

Weight of cement = 1.41612kg

Weight of fine aggregates =2.13221kg

Weight of coarse aggregates = 4.22705kg

<u>Weight of cement and ash for the replacements</u>

To simplify the calculation, the specific gravity of cement and ash are assumed to be equal.

For X% Replacement,

Weight of cement = $\frac{100-X}{100}\ X\ weight\ of\ cement\ at\ 0\%$

Weight of ash = $\frac{X}{100}\ X\ weight\ of\ cement\ at\ 0\%$

<u>Weight of constant concrete constituents</u>

Number of cubes for one replacement = curing periods x trial cubes = 6 x 3 = 18cubes.

Recall that weight of water = 0.84696kg

1 cube = 0.84696kg

18cubes = 18 x 0.84696kg = 15.25kg

Weight of fine aggregate = 18 x 2.13221 =38.38kg

Weight of coarse aggregate = 18 x 4.22705 = 76.09kg

<u>Weight of cement at 0%</u>

$$Water/cement\ ratio = \frac{w}{c} = 0.6$$

$$c = \frac{w}{0.6} = \frac{15.25}{0.6} = 25.42kg$$

Mix Proportion of Concrete Constituents

Mix ratio: **1: 1.5: 3** (Cement: Sand: Granite)

For 1.5% Replacement; $\frac{1.5}{100}\ x\ 1 = 0.015\ (Ash)$

1-0.015 = 0.985 (Cement)

Mix Proportion for 1.5% NCPA Replacement

= 0.985:0.015:1.5:3 (Cement: Ash: Sand: Granite)

This is applied to all other % NCPA replacement

The mix proportions of constituent materials of the concrete are shown in Table 1

APPENDIX E: Mix proportion

Table 1: Mix Proportion of Constituent Materials for the Concrete Production

Mixture Label	Mix Proportions	Water (kg)	Cement (kg)	NCPA (kg)	Sand (kg)	Granite (kg)
A1	1.000: 0.000: 1.5:3	15.25	25.42	0.00	38.38	76.09
A2	0.985: 0.015: 1.5:3	15.25	25.04	0.38	38.38	76.09
A3	0.970: 0.030: 1.5:3	15.25	24.66	0.76	38.38	76.09
A4	0.955: 0.045: 1.5:3	15.25	24.28	1.14	38.38	76.09
A5	0.940: 0.060: 1.5:3	15.25	23.89	1.53	38.38	76.09
A6	0.925: 0.075: 1.5:3	15.25	23.51	1.91	38.38	76.09
A7	0.910: 0.090: 1.5:3	15.25	23.13	2.29	38.38	76.09
A8	0.895: 0.105: 1.5:3	15.25	22.75	2.67	38.38	76.09
A9	0.880: 0120: 1.5: 3	15.25	22.37	3.05	38.38	76.09
A10	0.865: 0.135: 1.5:3	15.25	21.99	3.43	38.38	76.09
A11	0.850: 0.150: 1.5:3	15.25	21.61	3.81	38.38	76.09
A12	0.835: 0.165: 1.5:3	15.25	21.23	4.19	38.38	76.09
A13	0.820: 0.180: 1.5:3	15.25	20.84	4.58	38.38	76.09
A14	0.805: 0.195: 1.5:3	15.25	20.46	4.96	38.38	76.09
A15	0.790: 0.210: 1.5:3	15.25	20.08	5.34	38.38	76.09
A16	0.775: 0.225: 1.5:3	15.25	19.70	5.72	38.38	76.09
A17	0.760: 0.240: 1.5:3	15.25	19.32	6.10	38.38	76.09
A18	0.745: 0.255: 1.5:3	15.25	18.94	6.48	38.38	76.09
A19	0.730: 0.270: 1.5:3	15.25	18.56	6.86	38.38	76.09
A20	0.715: 0.285: 1.5:3	15.25	18.18	7.24	38.38	76.09
A21	0.700: 0.300: 1.5:3	15.25	17.79	7.63	38.38	76.09
A22	0.685: 0.315: 1.5:3	15.25	17.41	8.01	38.38	76.09
A23	0.670: 0.330: 1.5:3	15.25	17.03	8.39	38.38	76.09
A24	0.655: 0.345: 1.5:3	15.25	16.65	8.77	38.38	76.09
A25	0.640: 0.360: 1.5:3	15.25	16.27	9.15	38.38	76.09
A26	0.625: 0.375: 1.5:3	15.25	15.89	9.53	38.38	76.09
A27	0.610: 0.390: 1.5:3	15.25	15.51	9.91	38.38	76.09
A28	0.595: 0.405: 1.5:3	15.25	15.12	10.30	38.38	76.09
A29	0.580: 0.420: 1.5:3	15.25	14.74	10.68	38.38	76.09
A30	0.565: 0.435: 1.5:3	15.25	14.36	11.06	38.38	76.09
A31	0.550: 0.450: 1.5:3	15.25	13.98	11.44	38.38	76.09
A32	0.535: 0.465: 1.5:3	15.25	13.60	11.82	38.38	76.09
A33	0.520:0.480: 1.5:3	15.25	13.22	12.20	38.38	76.09
A34	0.505: 0.495: 1.5:3	15.25	12.84	12.58	38.38	76.09
A35	0.490: 0.510: 1.5:3	15.25	12.46	12.96	38.38	76.09
A36	0.475: 0.525: 1.5:3	15.25	12.07	13.35	38.38	76.09
A37	0.460: 0.540: 1.5:3	15.25	11.69	13.73	38.38	76.09
A38	0.445: 0.555: 1.5:3	15.25	11.31	14.11	38.38	76.09
A39	0.430: 0.570: 1.5:3	15.25	10.93	14.49	38.38	76.09
A40	0.415: 0.585: 1.5:3	15.25	10.55	14.87	38.38	76.09
A41	0.400: 0.600: 1.5:3	15.25	10.17	15.25	38.38	76.09
A42	0.385: 0.615: 1.5:3	15.25	9.79	15.63	38.38	76.09
A43	0.370: 0.630: 1.5:3	15.25	9.41	16.01	38.38	76.09
A44	0.355: 0.645: 1.5:3	15.25	9.02	16.40	38.38	76.09
A45	0.340: 0.660: 1.5:3	15.25	8.64	16.78	38.38	76.09
A46	0.325: 0.675: 1.5:3	15.25	8.26	17.16	38.38	76.09
A47	0.310: 0.690: 1.5:3	15.25	7.88	17.54	38.38	76.09
A48	0.295: 0.705: 1.5:3	15.25	7.50	17.92	38.38	76.09
A49	0.280: 0.720: 1.5:3	15.25	7.12	18.30	38.38	76.09
A50	0.265: 0.735: 1.5:3	15.25	6.74	18.68	38.38	76.09
A51	0.250: 0.750: 1.5:3	15.25	6.36	19.07	38.38	76.09

APPENDIX E (Continued)

Table 2. Mix Proportion and Compressive strength of NCPA-Cement Concrete

S/No	Mixture Label	Portland cement	NCPA	Sand	Granite	Water-cement	Mix Proportions	7th day	14th day	28th day	56th day
1	A1	1	0	1.5	3	0.60	1.000: 0.000: 1.5:3	15.30	18.60	20.50	25.90
2	A2	0.985	0.015	1.5	3	0.61	0.985: 0.015: 1.5:3	15.50	18.90	20.80	26.30
3	A3	0.970	0.030	1.5	3	0.62	0.970: 0.030: 1.5:3	15.60	19.20	21.20	26.50
4	A4	0.955	0.045	1.5	3	0.63	0.955: 0.045: 1.5:3	15.90	19.60	21.50	27.40
5	A5	0.940	0.060	1.5	3	0.64	0.940: 0.060: 1.5:3	16.10	19.90	21.80	27.60
6	A6	0.925	0.075	1.5	3	0.65	0.925: 0.075: 1.5:3	16.30	20.10	22.20	27.90
7	A7	0.910	0.090	1.5	3	0.66	0.910: 0.090: 1.5:3	16.60	20.40	22.50	28.10
8	A8	0.895	0.105	1.5	3	0.67	0.895: 0.105: 1.5:3	17.10	20.60	22.70	28.30
9	A9	0.880	0.120	1.5	3	0.68	0.880: 0120: 1.5:3	17.40	20.90	23.00	28.60
10	A10	0.865	0.135	1.5	3	0.69	0.865: 0.135: 1.5:3	17.60	21.30	23.10	29.00
11	A11	0.850	0.150	1.5	3	0.71	0.850: 0.150: 1.5:3	17.90	21.50	23.40	29.20
12	A12	0.835	0.165	1.5	3	0.72	0.835: 0.165: 1.5:3	18.20	21.60	23.70	29.40
13	A13	0.820	0.180	1.5	3	0.73	0.820:0.180: 1.5:3	18.50	21.90	24.00	30.00
s14	A14	0.805	0.195	1.5	3	0.75	0.805: 0.195: 1.5:3	18.70	22.10	24.20	30.10
15	A15	0.790	0.210	1.5	3	0.76	0.790: 0.210: 1.5:3	17.20	21.70	23.60	29.70
16	A16	0.775	0.225	1.5	3	0.77	0.775: 0.225: 1.5:3	16.80	20.90	23.30	29.50
17	A17	0.760	0.240	1.5	3	0.79	0.760: 0.240: 1.5:3	16.50	20.50	23.10	29.40
18	A18	0.745	0.255	1.5	3	0.81	0.745: 0.255: 1.5:3	16.10	20.30	22.90	28.60
19	A19	0.730	0.270	1.5	3	0.82	0.730: 0.270: 1.5:3	15.90	20.10	22.60	28.50
20	A20	0.715	0.285	1.5	3	0.84	0.715: 0.285: 1.5:3	15.60	19.80	22.50	28.40
21	A21	0.700	0.300	1.5	3	0.86	0.700: 0.300: 1.5:3	15.10	19.60	22.30	28.10
22	A22	0.685	0.315	1.5	3	0.88	0.685: 0.315: 1.5:3	14.70	19.30	22.00	27.90
23	A23	0.670	0.330	1.5	3	0.90	0.670: 0.330: 1.5:3	14.30	19.10	21.70	27.80
24	A24	0.655	0.345	1.5	3	0.92	0.655: 0.345: 1.5:3	14.10	18.70	21.60	27.50
25	A25	0.640	0.360	1.5	3	0.94	0.640: 0.360: 1.5:3	13.60	18.50	21.10	26.90
26	A26	0.625	0.375	1.5	3	0.96	0.625: 0.375: 1.5:3	13.40	18.30	20.70	26.50
27	A27	0.610	0.390	1.5	3	0.98	0.610: 0.390: 1.5:3	13.10	17.70	20.50	26.10
28	A28	0.595	0.405	1.5	3	1.01	0.595: 0.405: 1.5:3	12.50	17.50	20.20	24.90
29	A29	0.580	0.420	1.5	3	1.03	0.580: 0.420: 1.5:3	12.10	16.60	19.30	24.60
30	A30	0.565	0.435	1.5	3	1.06	0.565: 0.435: 1.5:3	11.80	16.30	19.00	23.90
31	A31	0.550	0.450	1.5	3	1.09	0.550: 0.450: 1.5:3	11.30	16.10	18.70	23.80
32	A32	0.535	0.465	1.5	3	1.12	0.535: 0.465: 1.5:3	10.90	15.40	18.30	23.40
33	A33	0.520	0.480	1.5	3	1.15	0.520:0.480: 1.5:3	10.50	15.20	18.10	23.10
34	A34	0.505	0.495	1.5	3	1.19	0.505: 0.495: 1.5:3	10.20	14.90	17.30	22.70
35	A35	0.490	0.510	1.5	3	1.22	0.490: 0.510: 1.5:3	9.90	14.70	17.10	22.70
36	A36	0.475	0.525	1.5	3	1.26	0.475: 0.525: 1.5:3	9.60	14.50	16.50	21.80
37	A37	0.460	0.540	1.5	3	1.30	0.460: 0.540: 1.5:3	9.40	13.80	16.30	21.60
38	A38	0.445	0.555	1.5	3	1.35	0.445: 0.555: 1.5:3	9.30	13.60	16.10	20.90
39	A39	0.430	0.570	1.5	3	1.40	0.430: 0.570: 1.5:3	8.80	13.30	16.00	20.70
40	A40	0.415	0.585	1.5	3	1.45	0.415: 0.585: 1.5:3	8.60	13.00	15.80	20.50
41	A41	0.400	0.600	1.5	3	1.50	0.400:0.600: 1.5:3	8.30	12.80	15.60	20.20
42	A42	0.385	0.615	1.5	3	1.56	0.385: 0.615: 1.5:3	8.10	12.70	15.10	19.90
43	A43	0.370	0.630	1.5	3	1.62	0.370: 0.630: 1.5:3	7.80	12.50	14.90	19.60
44	A44	0.355	0.645	1.5	3	1.69	0.355: 0.645: 1.5:3	7.60	12.30	14.60	19.30
45	A45	0.340	0.660	1.5	3	1.77	0.340: 0.660: 1.5:3	7.30	11.90	14.30	18.90
46	A46	0.325	0.675	1.5	3	1.85	0.325: 0.675: 1.5:3	7.10	11.70	14.00	18.50
47	A47	0.310	0.690	1.5	3	1.94	0.310: 0.690: 1.5:3	6.70	11.60	13.70	18.10
48	A48	0.295	0.705	1.5	3	2.03	0.295: 0.705: 1.5:3	6.40	11.40	13.50	16.90
49	A49	0.280	0.720	1.5	3	2.14	0.280: 0.720: 1.5:3	6.20	10.90	13.20	16.40
50	A50	0.265	0.735	1.5	3	2.26	0.265: 0.735: 1.5:3	5.70	10.70	12.60	15.50
51	A51	0.250	0.750	1.5	3	2.40	0.250: 0.750: 1.5:3	5.30	10.30	12.30	15.20

APPENDIX F: Slump of NCPA-cement concrete

Table 3. Variation of Slump of NCPA-Cement Concrete

NCPA % Replacement	Slump of Concrete (mm)
0.0	32.0
1.5	33.4
3.0	33.8
4.5	34.0
6.0	34.5
7.5	34.7
9.0	35.1
10.5	35.6
12.0	35.8
13.5	36.0
15.0	36.3
16.5	36.8
18.0	38.0
19.5	38.4
21.0	38.7
22.5	40.0
24.0	40.2
25.5	40.6
27.0	40.8
28.5	41.3
30.0	41.5
31.5	41.8
33.0	42.2
34.5	42.5
36.0	42.8
37.5	43.0
39.0	43.5
40.5	43.7
42.0	45.0
43.5	45.2
45.0	45.4
46.5	45.8
48.0	46.0
49.5	46.2
51.0	46.5
52.5	47.0
54.0	47.2
55.5	47.6
57.0	48.4
58.5	48.8
60.0	49.0
61.5	49.4
63.0	49.7
64.5	50.0
66.0	50.2
67.5	50.4
69.0	51.8
70.5	52.5
72.0	53.0
73.5	54.2
75.0	55.8

APPENDIX G: Setting times

Table 4. Variation of Initial and Final Setting Times with Cement Partial Replacement

NCPA % Replacement	Initial Setting time (mins)	Final Setting time (mins)
0.0	50	110
1.5	55	125
3.0	60	140
4.5	65	150
6.0	70	155
7.5	75	170
9.0	80	180
10.5	85	195
12.0	90	205
13.5	95	215
15.0	100	225
16.5	105	235
18.0	110	245
19.5	115	255
21.0	120	260
22.5	125	270
24.0	130	275
25.5	135	290
27.0	140	295
28.5	145	305
30.0	150	320
31.5	155	330
33.0	160	335
34.5	165	345
36.0	170	355
37.5	175	365
39.0	180	370
40.5	185	380
42.0	190	385
43.5	195	395
45.0	200	410
46.5	205	420
48.0	210	435
49.5	215	445
51.0	220	455
52.5	225	460
54.0	230	465
55.5	235	475
57.0	240	490
58.5	245	500
60.0	250	515
61.5	255	520
63.0	260	530
64.5	265	535
66.0	270	545
67.5	275	550
69.0	280	565
70.5	285	575
72.0	290	580
73.5	295	590
75.0	300	605

APPENDIX H: Compressive strength results for different curing ages

Table 5. Result of Compressive Strength for 7days

Compressive Strength Result for 7days				
% Replacement	**Sample 1**	**Sample 2**	**Sample 3**	**Average Strength**
%	N/mm^2	N/mm^2	N/mm^2	N/mm^2
0.0	15.21	15.31	15.34	**15.30**
1.5	15.60	15.55	15.65	**15.50**
3.0	15.38	15.70	15.72	**15.60**
4.5	16.10	15.80	15.80	**15.90**
6.0	15.85	16.50	15.95	**16.10**
7.5	16.60	16.10	16.20	**16.30**
9.0	17.00	16.50	16.30	**16.60**
10.5	16.90	17.22	17.18	**17.10**
12.0	17.65	17.24	17.30	**17.40**
13.5	17.52	17.52	17.76	**17.60**
15.0	18.20	17.95	17.55	**17.90**
16.5	17.80	18.22	18.58	**18.20**
18.0	19.10	18.18	18.22	**18.50**
19.5	18.38	19.20	18.52	**18.70**
21.0	17.48	16.48	17.64	**17.20**
22.5	16.52	16.34	17.54	**16.80**
24.0	16.42	16.30	16.78	**16.50**
25.5	15.30	16.62	16.38	**16.10**
27.0	16.40	15.68	15.62	**15.90**
28.5	15.80	15.30	15.70	**15.60**
30.0	14.40	15.80	15.10	**15.10**
31.5	14.82	15.04	14.24	**14.70**
33.0	14.54	14.46	13.90	**14.30**
34.5	13.82	14.30	14.18	**14.10**
36.0	13.85	13.30	13.65	**13.60**
37.5	13.64	13.24	13.32	**13.40**
39.0	12.45	13.51	13.34	**13.10**
40.5	12.62	12.28	12.60	**12.50**
42.0	11.60	12.60	12.10	**12.10**
43.5	11.52	11.68	12.20	**11.80**
45.0	10.55	11.90	11.45	**11.30**
46.5	10.96	11.66	10.08	**10.90**
48.0	9.84	10.70	10.96	**10.50**
49.5	10.57	10.06	9.97	**10.20**
51.0	9.45	9.65	10.60	**9.90**
52.5	9.00	10.30	9.50	**9.60**
54.0	9.10	10.04	9.06	**9.40**
55.5	9.20	9.56	9.14	**9.30**

57.0	8.90	9.20	8.30	**8.80**
58.5	8.70	8.67	8.43	**8.60**
60.0	8.54	8.22	8.14	**8.30**
61.5	7.60	8.64	8.06	**8.10**
63.0	8.50	7.66	8.50	**7.80**
64.5	7.30	8.22	7.28	**7.60**
66.0	7.14	7.12	7.64	**7.30**
67.5	6.56	7.72	7.02	**7.10**
69.0	6.44	6.85	6.82	**6.70**
70.5	7.01	6.08	6.11	**6.40**
72.0	6.12	6.20	6.28	**6.20**
73.5	5.20	6.50	5.40	**5.70**
75.0	5.04	5.74	5.12	**5.30**

APPENDIX H: Compressive strength results (Continued)

Table 6. Result of Compressive Strength for 14days

Compressive Strength Result for 14days				
% Replacement	**Sample 1**	**Sample 2**	**Sample 3**	**Average Strength**
%	N/mm^2	N/mm^2	N/mm^2	N/mm^2
0.0	18.35	18.45	19.00	**18.60**
1.5	19.02	19.36	18.32	**18.90**
3.0	19.33	19.40	18.87	**19.20**
4.5	19.36	20.28	19.16	**19.60**
6.0	20.28	20.22	19.20	**19.90**
7.5	20.02	20.74	19.54	**20.10**
9.0	20.82	20.10	20.28	**20.40**
10.5	20.24	20.74	20.82	**20.60**
12.0	20.94	21.36	20.40	**20.90**
13.5	21.21	21.34	21.35	**21.30**
15.0	20.91	21.74	21.85	**21.50**
16.5	21.22	21.38	22.20	**21.60**
18.0	21.77	21.25	22.68	**21.90**
19.5	21.30	21.72	23.28	**22.10**
21.0	20.95	21.28	22.87	**21.70**
22.5	20.74	20.96	21.00	**20.90**
24.0	20.84	20.02	20.64	**20.50**
25.5	19.82	20.70	20.38	**20.30**
27.0	20.14	20.43	19.73	**20.10**
28.5	19.52	20.60	19.28	**19.80**
30.0	19.15	20.25	19.40	**19.60**
31.5	19.80	19.00	19.10	**19.30**
33.0	19.14	19.12	19.04	**19.10**
34.5	18.94	18.12	19.04	**18.70**
36.0	18.30	18.01	19.19	**18.50**
37.5	18.15	18.57	18.18	**18.30**
39.0	17.92	17.54	17.64	**17.70**
40.5	16.88	17.66	17.96	**17.50**
42.0	16.92	16.76	16.12	**16.60**
43.5	16.32	16.43	16.15	**16.30**
45.0	16.20	16.02	16.08	**16.10**
46.5	15.12	15.10	15.98	**15.40**
48.0	15.35	15.24	15.01	**15.20**
49.5	14.80	14.60	15.30	**14.90**
51.0	14.55	14.73	14.82	**14.70**
52.5	14.90	14.20	14.40	**14.50**
54.0	13.65	13.75	14.00	**13.80**
55.5	13.10	14.10	13.60	**13.60**

57.0	13.80	12.90	13.20	**13.30**
58.5	12.93	12.66	13.41	**13.00**
60.0	12.54	12.78	13.08	**12.80**
61.5	12.64	12.58	12.88	**12.70**
63.0	12.69	12.37	12.44	**12.50**
64.5	12.00	12.55	12.35	**12.30**
66.0	12.18	11.64	11.88	**11.90**
67.5	11.44	11.70	11.96	**11.70**
69.0	11.38	11.65	11.77	**11.60**
70.5	11.52	11.54	11.14	**11.40**
72.0	10.50	11.25	10.95	**10.90**
73.5	10.70	11.10	10.30	**10.70**
75.0	10.80	10.24	9.86	**10.30**

APPENDIX H: Compressive strength results (Continued)

Table 7. Result of Compressive Strength for 28days

Compressive Strength Result for 28days				
% Replacement	Sample 1	Sample 2	Sample 3	Average Strength
%	N/mm^2	N/mm^2	N/mm^2	N/mm^2
0.0	20.45	20.10	20.95	**20.50**
1.5	21.46	20.66	20.28	**20.80**
3.0	21.55	21.35	20.70	**21.20**
4.5	21.80	21.50	21.20	**21.50**
6.0	21.67	21.05	22.68	**21.80**
7.5	22.38	22.12	22.10	**22.20**
9.0	22.30	22.68	22.52	**22.50**
10.5	23.21	22.58	22.31	**22.70**
12.0	23.80	23.10	22.10	**23.00**
13.5	23.94	23.12	22.24	**23.10**
15.0	23.34	23.18	23.68	**23.40**
16.5	24.30	23.62	23.18	**23.70**
18.0	24.18	24.02	23.80	**24.00**
19.5	24.52	24.48	23.60	**24.20**
21.0	23.55	23.52	23.73	**23.60**
22.5	22.80	23.50	23.60	**23.30**
24.0	23.00	23.50	22.80	**23.10**
25.5	22.87	23.05	22.78	**22.90**
27.0	22.98	22.84	21.98	**22.60**
28.5	23.10	22.30	22.10	**22.50**
30.0	22.30	22.00	22.60	**22.30**
31.5	22.80	21.60	21.60	**22.00**
33.0	21.94	21.62	21.54	**21.70**
34.5	21.56	21.60	21.64	**21.60**
36.0	20.80	21.20	21.30	**21.10**
37.5	20.08	20.68	21.34	**20.70**
39.0	21.12	20.22	20.16	**20.50**
40.5	20.32	20.18	20.10	**20.20**
42.0	19.44	19.28	19.18	**19.30**
43.5	19.08	18.88	19.04	**19.00**
45.0	18.22	18.58	19.30	**18.70**
46.5	18.15	18.43	18.32	**18.30**
48.0	18.28	18.12	17.90	**18.10**
49.5	18.50	17.10	16.30	**17.30**
51.0	17.06	17.16	17.08	**17.10**
52.5	16.88	16.66	15.96	**16.50**
54.0	16.25	16.30	16.35	**16.30**
55.5	16.84	15.60	15.86	**16.10**

57.0	15.90	15.88	16.22	**16.00**
58.5	16.22	15.50	15.68	**15.80**
60.0	15.85	15.65	15.30	**15.60**
61.5	15.32	15.26	14.72	**15.10**
63.0	14.50	15.40	14.80	**14.90**
64.5	14.85	14.58	14.37	**14.60**
66.0	14.02	14.70	14.18	**14.30**
67.5	14.40	13.90	13.70	**14.00**
69.0	14.10	13.36	13.64	**13.70**
70.5	13.76	13.86	12.88	**13.50**
72.0	13.38	13.54	12.68	**13.20**
73.5	12.30	12.50	13.00	**12.60**
75.0	12.06	12.24	12.60	**12.30**

APPENDIX H: Compressive strength results (Continued)

Table 8. Result of Compressive Strength for 56days

Compressive Strength Result for 56days				
% Replacement	**Sample 1**	**Sample 2**	**Sample 3**	**Average Strength**
%	N/mm^2	N/mm^2	N/mm^2	N/mm^2
0.0	24.75	26.64	26.31	**25.90**
1.5	26.40	26.14	26.36	**26.30**
3.0	27.30	26.04	26.16	**26.50**
4.5	28.04	27.16	27.00	**27.40**
6.0	27.54	27.58	27.68	**27.60**
7.5	28.02	27.38	28.30	**27.90**
9.0	28.24	28.46	27.60	**28.10**
10.5	27.60	28.70	28.60	**28.30**
12.0	29.10	28.30	28.40	**28.60**
13.5	28.80	29.12	29.08	**29.00**
15.0	29.05	29.25	29.30	**29.20**
16.5	29.50	29.40	29.30	**29.40**
18.0	31.10	29.25	29.65	**30.00**
19.5	31.11	30.10	29.09	**30.10**
21.0	28.97	29.83	30.30	**29.70**
22.5	29.65	30.25	28.60	**29.50**
24.0	29.72	29.20	29.28	**29.40**
25.5	28.45	29.15	28.50	**28.60**
27.0	28.30	29.02	28.18	**28.50**
28.5	29.10	28.20	27.90	**28.40**
30.0	28.70	28.50	27.10	**28.10**
31.5	27.20	28.00	28.50	**27.90**
33.0	26.92	28.30	28.18	**27.80**
34.5	27.30	27.70	27.50	**27.50**
36.0	27.27	26.78	26.65	**26.90**
37.5	26.60	27.25	25.65	**26.50**
39.0	26.15	26.01	26.14	**26.10**
40.5	26.24	24.80	23.66	**24.90**
42.0	24.80	24.80	24.20	**24.60**
43.5	23.65	24.30	23.75	**23.90**
45.0	23.92	23.60	23.88	**23.80**
46.5	24.54	23.54	22.12	**23.40**
48.0	23.68	22.45	23.17	**23.10**
49.5	22.80	22.12	23.18	**22.70**
51.0	22.70	21.60	23.80	**22.70**
52.5	21.64	22.94	20.82	**21.80**
54.0	21.30	22.40	21.10	**21.60**
55.5	20.76	21.32	20.62	**20.90**

57.0	20.57	20.68	20.85	**20.70**
58.5	20.56	20.44	20.50	**20.50**
60.0	20.30	19.58	20.72	**20.20**
61.5	19.55	20.04	20.11	**19.90**
63.0	20.10	19.50	19.20	**19.60**
64.5	19.44	19.22	19.24	**19.30**
66.0	18.65	18.75	19.30	**18.90**
67.5	18.35	18.62	18.53	**18.50**
69.0	18.15	18.10	18.05	**18.10**
70.5	17.00	17.20	16.50	**16.90**
72.0	16.06	16.60	16.54	**16.40**
73.5	15.18	16.10	15.22	**15.50**
75.0	15.75	15.10	14.75	**15.20**

APPENDIX H: Compressive strength results (Continued)

Table 9. Result of Compressive Strength for 90days

Compressive Strength Result for 90days				
% Replacement	**Sample 1**	**Sample 2**	**Sample 3**	**Average Strength**
%	N/mm^2	N/mm^2	N/mm^2	N/mm^2
0.0	28.12	27.80	27.18	**27.70**
1.5	28.14	28.16	28.00	**28.10**
3.0	28.20	28.40	28.30	**28.30**
4.5	28.70	28.35	28.45	**28.50**
6.0	29.05	28.95	28.70	**28.90**
7.5	29.30	29.15	29.15	**29.20**
9.0	30.18	29.16	29.46	**29.60**
10.5	29.85	30.12	29.73	**29.90**
12.0	31.06	31.54	30.40	**31.00**
13.5	31.53	31.95	30.42	**31.30**
15.0	32.40	31.54	31.16	**31.70**
16.5	31.70	32.20	31.80	**31.90**
18.0	34.60	32.80	31.90	**33.10**
19.5	33.80	33.40	32.70	**33.30**
21.0	32.78	33.12	32.50	**32.80**
22.5	31.65	31.55	31.60	**31.60**
24.0	31.32	31.24	31.34	**31.30**
25.5	30.60	31.00	30.50	**30.70**
27.0	31.10	30.30	30.10	**30.50**
28.5	30.34	30.31	29.95	**30.20**
30.0	29.30	30.70	29.70	**29.90**
31.5	30.05	29.55	29.50	**29.70**
33.0	29.65	29.15	29.10	**29.30**
34.5	28.62	28.34	28.54	**28.50**
36.0	28.40	28.20	28.30	**28.30**
37.5	27.90	28.02	28.08	**28.00**
39.0	27.70	27.85	28.15	**27.90**
40.5	27.40	27.50	27.60	**27.50**
42.0	27.05	27.25	27.30	**27.20**
43.5	27.10	26.80	26.50	**26.80**
45.0	26.35	26.70	26.45	**26.50**
46.5	25.45	26.45	25.80	**25.90**
48.0	25.58	25.62	25.90	**25.70**
49.5	25.44	23.80	24.26	**24.50**
51.0	24.56	24.40	23.34	**24.10**
52.5	24.08	23.32	24.30	**23.90**
54.0	23.16	23.18	24.16	**23.50**
55.5	23.85	23.70	23.85	**23.80**

57.0	22.46	23.20	22.44	**22.70**
58.5	22.15	22.24	22.51	**22.30**
60.0	22.52	21.70	21.48	**21.90**
61.5	22.05	21.45	21.30	**21.60**
63.0	20.84	21.34	21.72	**21.30**
64.5	20.90	21.30	20.80	**21.00**
66.0	21.07	20.80	20.83	**20.90**
67.5	20.25	20.85	20.70	**20.60**
69.0	19.80	20.30	20.20	**20.10**
70.5	20.26	19.64	19.20	**19.70**
72.0	19.60	18.80	19.80	**19.40**
73.5	19.16	18.14	18.50	**18.60**
75.0	18.65	17.85	17.20	**17.90**

APPENDIX H: Compressive strength results (Continued)

Table 10. Results of Compressive Strength for 150days

Compressive Strength Result for 150days				
% Replacement	**Sample 1**	**Sample 2**	**Sample 3**	**Average Strength**
%	N/mm^2	N/mm^2	N/mm^2	N/mm^2
0.0	32.50	31.60	31.30	**31.80**
1.5	33.20	32.70	31.60	**32.50**
3.0	33.56	32.50	32.34	**32.80**
4.5	33.56	32.90	33.85	**33.40**
6.0	34.25	33.65	33.20	**33.70**
7.5	34.30	33.60	34.70	**34.20**
9.0	35.65	34.60	33.25	**34.50**
10.5	34.60	35.36	34.44	**34.80**
12.0	35.05	35.20	34.75	**35.00**
13.5	35.60	35.20	34.50	**35.10**
15.0	35.30	35.45	35.15	**35.30**
16.5	35.65	36.15	35.30	**35.70**
18.0	37.20	36.12	36.18	**36.50**
19.5	37.15	37.20	36.35	**36.90**
21.0	36.25	35.70	34.85	**35.60**
22.5	35.33	35.22	35.05	**35.20**
24.0	34.45	34.30	34.15	**34.30**
25.5	33.20	34.30	34.20	**33.90**
27.0	33.60	33.60	33.30	**33.50**
28.5	33.66	31.86	32.58	**32.70**
30.0	32.08	32.12	32.10	**32.10**
31.5	31.52	30.40	30.78	**30.90**
33.0	30.35	31.10	29.45	**30.30**
34.5	29.24	30.34	29.52	**29.70**
36.0	29.84	28.70	29.66	**29.40**
37.5	29.65	29.25	28.70	**29.20**
39.0	28.65	28.55	29.50	**28.90**
40.5	28.45	29.15	28.50	**28.70**
42.0	27.70	28.35	28.85	**28.30**
43.5	27.85	28.10	28.05	**28.00**
45.0	28.52	27.50	26.78	**27.60**
46.5	27.65	27.35	27.20	**27.40**
48.0	27.35	27.15	26.80	**27.10**
49.5	26.82	26.28	27.60	**26.90**
51.0	25.60	26.20	27.10	**26.30**
52.5	26.25	25.80	25.65	**25.90**
54.0	26.20	25.40	25.20	**25.60**
55.5	25.26	25.24	25.40	**25.30**

57.0	24.76	25.30	24.64	**24.90**
58.5	24.70	24.80	24.90	**24.80**
60.0	24.05	23.48	23.57	**23.70**
61.5	22.50	24.70	23.60	**23.60**
63.0	23.40	22.76	23.44	**23.20**
64.5	24.08	23.42	22.10	**23.00**
66.0	23.64	22.85	22.21	**22.80**
67.5	23.34	23.10	22.12	**22.50**
69.0	22.28	21.90	21.65	**21.90**
70.5	22.15	21.92	21.56	**21.60**
72.0	21.34	21.30	21.26	**21.30**
73.5	20.48	21.12	20.50	**20.70**
75.0	20.60	20.44	19.86	**20.30**

APPENDIX H: Compressive strength results (Continued)

Table 11. Results of the NCPA-Concrete Compressive Strength

% NCPA Replacement	Compressive Strength (N/mm^2)					
	7days	14days	28days	56days	90days	150days
0.0	15.30	18.60	20.50	25.90	27.70	31.80
1.5	15.50	18.90	20.80	26.30	28.10	32.50
3.0	15.60	19.20	21.20	26.50	28.30	32.80
4.5	15.90	19.60	21.50	27.40	28.50	33.40
6.0	16.10	19.90	21.80	27.60	28.90	33.70
7.5	16.30	20.10	22.20	27.90	29.20	34.20
9.0	16.60	20.40	22.50	28.10	29.60	34.50
10.5	17.10	20.60	22.70	28.30	29.90	34.80
12.0	17.40	20.90	23.00	28.60	31.00	35.00
13.5	17.60	21.30	23.10	29.00	31.30	35.10
15.0	17.90	21.50	23.40	29.20	31.70	35.30
16.5	18.20	21.60	23.70	29.40	31.90	35.70
18.0	18.50	21.90	24.00	30.00	33.10	36.50
19.5	18.70	22.10	24.20	30.10	33.30	36.90
21.0	17.20	21.70	23.60	29.70	32.80	35.60
22.5	16.80	20.90	23.30	29.50	31.60	35.20
24.0	16.50	20.50	23.10	29.40	31.30	34.30
25.5	16.10	20.30	22.90	28.60	30.70	33.90
27.0	15.90	20.10	22.60	28.50	30.50	33.50
28.5	15.60	19.80	22.50	28.40	30.20	32.70
30.0	15.10	19.60	22.30	28.10	29.90	32.10
31.5	14.70	19.30	22.00	27.90	29.70	30.90
33.0	14.30	19.10	21.70	27.80	29.30	30.30
34.5	14.10	18.70	21.60	27.50	28.50	29.70
36.0	13.60	18.50	21.10	26.90	28.30	29.40
37.5	13.40	18.30	20.70	26.50	28.00	29.20
39.0	13.10	17.70	20.50	26.10	27.90	28.90
40.5	12.50	17.50	20.20	24.90	27.50	28.70
42.0	12.10	16.60	19.30	24.60	27.20	28.30
43.5	11.80	16.30	19.00	23.90	26.80	28.00
45.0	11.30	16.10	18.70	23.80	26.50	27.60
46.5	10.90	15.40	18.30	23.40	25.90	27.40
48.0	10.50	15.20	18.10	23.10	25.70	27.10
49.5	10.20	14.90	17.30	22.70	24.50	26.90
51.0	9.90	14.70	17.10	22.70	24.10	26.30
52.5	9.60	14.50	16.50	21.80	23.90	25.90
54.0	9.40	13.80	16.30	21.60	23.50	25.60
55.5	9.30	13.60	16.10	20.90	23.80	25.30
57.0	8.80	13.30	16.00	20.70	22.70	24.90
58.5	8.60	13.00	15.80	20.50	22.30	24.80
60.0	8.30	12.80	15.60	20.20	21.90	23.70
61.5	8.10	12.70	15.10	19.90	21.60	23.60
63.0	7.80	12.50	14.90	19.60	21.30	23.20
64.5	7.60	12.30	14.60	19.30	21.00	23.00
66.0	7.30	11.90	14.30	18.90	20.90	22.80
67.5	7.10	11.70	14.00	18.50	20.60	22.50
69.0	6.70	11.60	13.70	18.10	20.10	21.90
70.5	6.40	11.40	13.50	16.90	19.70	21.60
72.0	6.20	10.90	13.20	16.40	19.40	21.30
73.5	5.70	10.70	12.60	15.50	18.60	20.70
75.0	5.30	10.30	12.30	15.20	17.90	20.30

APPENDIX H: Compressive strength results (Continued)

Table 12. ANN Compressive Strength Prediction for the NCPA-Concrete

% NCPA Replacement	ANN Compressive Strength (N/mm^2)					
	7days	14days	28days	56days	90days	150days
0.0	15.339	18.642	21.235	24.171	27.345	32.324
1.5	15.712	18.915	21.438	26.243	28.146	32.390
3.0	16.210	19.457	21.845	26.435	28.240	32.671
4.5	16.015	19.374	21.346	27.346	28.340	33.329
6.0	16.320	19.834	21.569	27.578	28.458	33.586
7.5	16.219	19.834	22.546	27.546	29.562	34.124
9.0	17.021	20.423	22.522	27.835	29.456	34.236
10.5	17.122	20.524	22.655	28.543	30.231	34.540
12.0	17.424	20.776	23.234	28.722	31.456	34.898
13.5	17.512	21.345	23.164	29.359	31.234	35.349
15.0	17.850	21.564	23.885	28.885	31.652	35.126
16.5	17.910	21.339	23.562	29.658	31.826	35.711
18.0	17.212	21.748	24.458	30.359	33.231	36.414
19.5	17.920	22.240	24.336	30.487	33.234	36.846
21.0	17.384	21.864	23.580	29.629	32.760	35.566
22.5	16.801	20.865	23.265	29.703	31.348	35.530
24.0	17.210	20.480	23.156	29.645	31.730	34.213
25.5	16.453	20.236	21.656	28.345	30.621	34.760
27.0	15.926	19.820	22.634	28.128	30.431	33.312
28.5	15.451	19.438	22.356	28.846	29.984.	32.615
30.0	15.126	19.340	22.321	28.498	30.212	32.211
31.5	14.748	18.701	22.458	28.349	29.899	30.659
33.0	14.375	19.389	20.934	28.213	29.565	30.126
34.5	14.124	18.556	21.452	27.391	28.537	29.875
36.0	14.130	18.514	21.146	26.672	28.234	29.445
37.5	13.326	18.325	20.568	26.198	28.564	29.413
39.0	13.156	17.634	19.620	26.375	27.860	28.745
40.5	12.430	17.489	20.264	24.234	27.237	28.410
42.0	12.238	16.458	19.324	24.534	27.546	27.879
43.5	11.732	16.248	19.326	23.348	26.643	28.235
45.0	11.365	16.383	18.652	23.386	26.324	27.496
46.5	10.924	15.456	18.215	23.989	25.765	27.230
48.0	10.545	15.234	18.349	23.305	25.654	27.015
49.5	10.520	14.842	17.260	23.089	24.512	26.480
51.0	9.916	14.823	16.921	23.568	24.124	26.120
52.5	9.960	14.426	16.728	21.608	23.865	25.745
54.0	9.356	13.815	16.867	21.135	24.120	24.934
55.5	9.288	13.921	15.560	20.236	23.912	25.279
57.0	8.658	12.968	16.235	20.629	22.554	24.815
58.5	8.725	13.320	15.456	20.356	22.234	24.458
60.0	8.429	12.956	15.564	20.249	21.546	23.564
61.5	8.245	12.484	15.128	18.869	21.324	23.451
63.0	7.641	12.329	14.458	20.340	21.214	21.879
64.5	7.542	12.213	14.458	19.236	21.345	23.238
66.0	7.256	11.423	14.266	18.450	20.876	23.120
67.5	7.346	11.365	14.245	18.238	20.534	22.436
69.0	7.124	11.278	13.576	18.567	20.456	21.764
70.5	6.562	11.872	13.325	16.945	19.569	21.435
72.0	6.368	10.468	12.739	16.238	19.356	21.426
73.5	5.856	10.682	12.126	15.565	18.640	20.645
75.0	5.359	10.346	11.869	15.230	17.865	20.249

APPENDIX I: Statistical table for student's T-test

Table 13. Percentage points of the distribution (Statistical Table for Student T-test)

One tail	**P = 0.005**	**0.025**	**0.005**	**0.0005**
Two tail	**P = 0.10**	**0.05**	**0.01**	**0.001**
V =1	6.31	12.71	63.66	636.62
2	2.92	4.30	9.92	31.60
3	2.35	3.18	5.84	12.94
4	2.13	2.78	4.60	8.61
5	2.02	2.57	4.03	6.87
6	1.94	2.45	3.71	5.96
7	1.89	2.36	3.50	5.41
8	1.86	2.31	3.36	5.04
9	1.83	2.26	3.25	4.78
10	1.81	2.23	3.17	4.59
11	1.80	2.20	3.12	4.44
12	1.78	2.18	3.05	4.32
13	1.77	2.16	3.01	4.22
14	1.76	2.14	2.98	4.14
15	1.75	2.13	2.95	4.07
16	1.75	2.12	2.92	4.02
17	1.74	2.11	2.90	3.97
18	1.73	2.10	2.88	3.92
19	1.73	2.09	2.85	3.88
20	1.72	2.09	2.83	3.85
21	1.72	2.08	2.83	3.82
22	1.72	2.07	2.82	3.79
23	1.71	2.07	2.81	3.77
24	1.71	2.06	2.90	3.75
25	1.71	2.06	2.79	3.73
26	1.71	2.06	2.78	3.71
27	1.70	2.05	2.77	3.69
28	1.70	2.05	2.76	3.67
29	1.70	2.04	2.76	3.66
30	1.70	2.04	2.75	3.65
40	1.68	2.02	2.70	3.55
50	1.68	2.01	2.68	3.50
100	1.68	1.98	2.63	3.39
0	1.64	1.96	2.58	3.29

APPENDIX J: Artificial Neural Network Program

```
function varargout = NCPA(varargin)
% NCPA MATLAB code for NCPA.fig
%      NCPA, by itself, creates a new NCPA or raises the existing
%      singleton*.
%
%      H = NCPA returns the handle to a new NCPA or the handle to
%      the existing singleton*.
%
%      NCPA('CALLBACK',hObject,eventData,handles,...) calls the local
%      function named CALLBACK in NCPA.M with the given input arguments.
%
%      NCPA('Property','Value',...) creates a new NCPA or raises the
%      existing singleton*.  Starting from the left, property value pairs
are
%      applied to the GUI before NCPA_OpeningFcn gets called.  An
%      unrecognized property name or invalid value makes property
application
%      stop.  All inputs are passed to NCPA_OpeningFcn via varargin.
%
%      *See GUI Options on GUIDE's Tools menu.  Choose "GUI allows only one
%      instance to run (singleton)".
%
% See also: GUIDE, GUIDATA, GUIHANDLES

% Edit the above text to modify the response to help NCPA

% Last Modified by GUIDE v2.5 12-Dec-2022 05:44:26

% Begin initialization code - DO NOT EDIT
gui_Singleton = 1;
gui_State = struct('gui_Name',       mfilename, ...
                   'gui_Singleton',  gui_Singleton, ...
                   'gui_OpeningFcn', @NCPA_OpeningFcn, ...
                   'gui_OutputFcn',  @NCPA_OutputFcn, ...
                   'gui_LayoutFcn',  [] , ...
                   'gui_Callback',   []);
if nargin && ischar(varargin{1})
    gui_State.gui_Callback = str2func(varargin{1});
end

if nargout
    [varargout{1:nargout}] = gui_mainfcn(gui_State, varargin{:});
else
    gui_mainfcn(gui_State, varargin{:});
end
% End initialization code - DO NOT EDIT


% --- Executes just before NCPA is made visible.
function NCPA_OpeningFcn(hObject, eventdata, handles, varargin)
% This function has no output args, see OutputFcn.
% hObject    handle to figure
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)
% varargin   command line arguments to NCPA (see VARARGIN)

% Choose default command line output for NCPA
```

```
handles.output = hObject;

% Update handles structure
guidata(hObject, handles);

% UIWAIT makes NCPA wait for user response (see UIRESUME)
% uiwait(handles.figure1);


% --- Outputs from this function are returned to the command line.
function varargout = NCPA_OutputFcn(hObject, eventdata, handles)
% varargout  cell array for returning output args (see VARARGOUT);
% hObject    handle to figure
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)

% Get default command line output from handles structure
varargout{1} = handles.output;



function txtCem_Callback(hObject, eventdata, handles)
% hObject    handle to txtCem (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)

% Hints: get(hObject,'String') returns contents of txtCem as text
%        str2double(get(hObject,'String')) returns contents of txtCem as a
double


% --- Executes during object creation, after setting all properties.
function txtCem_CreateFcn(hObject, eventdata, handles)
% hObject    handle to txtCem (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    empty - handles not created until after all CreateFcns called

% Hint: edit controls usually have a white background on Windows.
%       See ISPC and COMPUTER.
if ispc && isequal(get(hObject,'BackgroundColor'),
get(0,'defaultUicontrolBackgroundColor'))
    set(hObject,'BackgroundColor','white');
end



function txtNCPA_Callback(hObject, eventdata, handles)
% hObject    handle to txtNCPA (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)

% Hints: get(hObject,'String') returns contents of txtNCPA as text
%        str2double(get(hObject,'String')) returns contents of txtNCPA as a
double


% --- Executes during object creation, after setting all properties.
function txtNCPA_CreateFcn(hObject, eventdata, handles)
```

```
% hObject    handle to txtNCPA (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    empty - handles not created until after all CreateFcns called

% Hint: edit controls usually have a white background on Windows.
%       See ISPC and COMPUTER.
if ispc && isequal(get(hObject,'BackgroundColor'),
get(0,'defaultUicontrolBackgroundColor'))
    set(hObject,'BackgroundColor','white');
end



function txtSand_Callback(hObject, eventdata, handles)
% hObject    handle to txtSand (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)

% Hints: get(hObject,'String') returns contents of txtSand as text
%        str2double(get(hObject,'String')) returns contents of txtSand as a
double


% --- Executes during object creation, after setting all properties.
function txtSand_CreateFcn(hObject, eventdata, handles)
% hObject    handle to txtSand (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    empty - handles not created until after all CreateFcns called

% Hint: edit controls usually have a white background on Windows.
%       See ISPC and COMPUTER.
if ispc && isequal(get(hObject,'BackgroundColor'),
get(0,'defaultUicontrolBackgroundColor'))
    set(hObject,'BackgroundColor','white');
end



function txtWater_Callback(hObject, eventdata, handles)
% hObject    handle to txtWater (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)

% Hints: get(hObject,'String') returns contents of txtWater as text
%        str2double(get(hObject,'String')) returns contents of txtWater as
a double


% --- Executes during object creation, after setting all properties.
function txtWater_CreateFcn(hObject, eventdata, handles)
% hObject    handle to txtWater (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    empty - handles not created until after all CreateFcns called

% Hint: edit controls usually have a white background on Windows.
%       See ISPC and COMPUTER.
if ispc && isequal(get(hObject,'BackgroundColor'),
get(0,'defaultUicontrolBackgroundColor'))
```

```
    set(hObject,'BackgroundColor','white');
end


% --- Executes on button press in pushbutton1.
function pushbutton1_Callback(hObject, eventdata, handles)
global compressiveStrengthNN;
global optimisedNN;
cem = str2double(get(handles.txtCem,'string'));
hydLim =str2double(get(handles.txtNCPA,'string'));
sand =str2double(get(handles.txtSand,'string'));
granite =str2double(get(handles.txtGranit,'string'));
water =str2double(get(handles.txtWater,'string'));
v = [cem hydLim sand granite water 7];
v2 = [cem hydLim sand granite water 14];
v3= [cem hydLim sand granite water 21];
v4= [cem hydLim sand granite water 28];
v5= [cem hydLim sand granite water 58];
v = v';
v2=v2';
v3=v3';
v4=v4';
simval1 = [7 sim(compressiveStrengthNN,v) sim(optimisedNN, v)];

simval2 = [14 sim(compressiveStrengthNN,v2) sim(optimisedNN,v2)];

simval3 = [21 sim(compressiveStrengthNN,v3) sim(optimisedNN,v3)];

simval4 = [28 sim(compressiveStrengthNN,v4) sim(optimisedNN,v4)];

data=[simval1;simval2;simval3;simval4];
set(handles.tb1,'data',data);


% --- Executes on button press in pushbutton2.
function pushbutton2_Callback(hObject, eventdata, handles)
set(handles.txtCem,'string','');
set(handles.txtNCPA,'string','');
set(handles.txtSand,'string','');
set(handles.txtGranit,'string','');
set(handles.txtWater,'string','');



function txtGranit_Callback(hObject, eventdata, handles)
% hObject    handle to txtGranit (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)

% Hints: get(hObject,'String') returns contents of txtGranit as text
%        str2double(get(hObject,'String')) returns contents of txtGranit as
a double


% --- Executes during object creation, after setting all properties.
function txtGranit_CreateFcn(hObject, eventdata, handles)
% hObject    handle to txtGranit (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
```

```
% handles    empty - handles not created until after all CreateFcns called

% Hint: edit controls usually have a white background on Windows.
%       See ISPC and COMPUTER.
if ispc && isequal(get(hObject,'BackgroundColor'),
get(0,'defaultUicontrolBackgroundColor'))
    set(hObject,'BackgroundColor','white');
end


% --- Executes on button press in checkbox1.
function checkbox1_Callback(hObject, eventdata, handles)
% hObject    handle to checkbox1 (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)

% Hint: get(hObject,'Value') returns toggle state of checkbox1


% --- Executes on button press in checkbox3.
function checkbox3_Callback(hObject, eventdata, handles)
% hObject    handle to checkbox3 (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)

% Hint: get(hObject,'Value') returns toggle state of checkbox3


% --------------------------------------------------------------------
function file_Callback(hObject, eventdata, handles)
% hObject    handle to file (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)


% --------------------------------------------------------------------
function Untitled_3_Callback(hObject, eventdata, handles)
% hObject    handle to Untitled_3 (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)


% --------------------------------------------------------------------
function createAnn_Callback(hObject, eventdata, handles)

global compressiveStrengthNN;
global inputs;
global NCPAcompressiveStrengthTargets;
global optimisedNN;


NCPAcompressiveStrengthTargets =[15.30; 18.60;  20.50;  25.90;15.50;
18.90;  20.80;...
26.30;15.60;19.20;21.20;    26.50;15.90;    19.60;  21.50;  27.40;16.10;...
19.90;  21.80;  27.60;16.30;    20.10;  22.20;  27.90;16.60;    20.40;
22.50;...
28.10;17.10 ;20.60; 22.70;  28.30;17.40;    20.90;  23.00;  28.60;17.60;
21.30;...
```

```
23.10;  29.00;17.90;    21.50;  23.40;  29.20;18.20;    21.60;  23.70;
29.40;18.50;...
21.90;  24.00;  30.00;18.70;    22.10;  24.20;  30.10;17.20;    21.70;
23.60;  29.70;...
16.80;  20.90;  23.30;  29.50;16.50;    20.50;  23.10;  29.40;16.10;
20.30;  22.90;...
28.60;15.90;    20.10;  22.60;  28.50;15.60;    19.80;  22.50;
28.40;15.10;    19.60;...
22.30;  28.10;14.70;    19.30;  22.00;  27.90;14.30;    19.10;  21.70;
27.80;14.10;...
18.70;  21.60;  27.50;13.60;    18.50;  21.10;  26.90;13.40;    18.30;
20.70;  26.50;...
13.10;  17.70;  20.50;  26.10;12.50;    17.50;  20.20; 24.90;12.10;
16.60;19.30;24.60;...
11.80;16.30;19.00;23.90;11.30;16.10;18.70;23.80;10.90;15.40;18.30;23.40;10.
50;15.20;18.10;...
23.10;10.20;14.90;17.30;22.70;9.90;14.70;17.10;22.70;9.60;14.50;16.50;21.80
;9.40;13.80;...
16.30;21.60;9.30;13.60;16.10;20.90;8.80;13.30;16.00;20.70;8.60;13.00;15.80;
20.50;8.30;...
12.80;15.60;20.20;8.10;12.70;15.10;19.90;7.80;12.50;14.90;19.60;7.60;12.30;
14.60;19.30;...
7.30;11.90;14.30;18.90;7.10;11.70;14.00;18.50;6.70;11.60;13.70;18.10;6.40;1
1.40;13.50;...
16.90;6.20;10.90;13.20;16.40;5.70;10.70;12.60;15.50;5.30;10.30;12.30;15.20]
;
```

```
inputs= [1 0 1.5 3 0.60 7; 1 0 1.5 3 0.60 14;1 0 1.5 3 0.60 28;1 0 1.5 3
0.60 56;...
0.985   0.015   1.5 3   0.61    7;0.985 0.015   1.5 3   0.61    14;0.985
...
0.015   1.5 3   0.61    28;0.985    0.015   1.5 3   0.61    56;...
0.970   0.030   1.5 3   0.62    7;0.970 0.030   1.5 3   0.62    14;...
0.970   0.030   1.5 3   0.62    28;0.970    0.030   1.5 3   0.62    56;...
0.955   0.045   1.5 3   0.63    7;0.955 0.045   1.5 3   0.63    14;...
0.955   0.045   1.5 3   0.63    28;0.955    0.045   1.5 3   0.63    56;...
0.940   0.060   1.5 3   0.64    7;0.940 0.060   1.5 3   0.64    14;...
0.940   0.060   1.5 3   0.64    28;0.940    0.060   1.5 3   0.64    56;...
0.925   0.075   1.5 3   0.65    7;0.925 0.075   1.5 3   0.65    14;...
0.925   0.075   1.5 3   0.65    28;0.925    0.075   1.5 3   0.65    56;...
0.910   0.090   1.5 3   0.66    7;0.910 0.090   1.5 3   0.66    14;...
0.910   0.090   1.5 3   0.66    28;0.910    0.090   1.5 3   0.66    56;...
0.895   0.105   1.5 3   0.67    7;0.895 0.105   1.5 3   0.67    14;...
0.895   0.105   1.5 3   0.67    28;0.895    0.105   1.5 3   0.67    56;...
0.880   0.120   1.5 3   0.68    7;0.880 0.120   1.5 3   0.68    14;...
0.880   0.120   1.5 3   0.68    28;0.880    0.120   1.5 3   0.68    56;...
0.865   0.135   1.5 3   0.69    7;0.865 0.135   1.5 3   0.69    14;...
0.865   0.135   1.5 3   0.69    28;0.865    0.135   1.5 3   0.69    56;...
0.850   0.150   1.5 3   0.71    7;0.850 0.150   1.5 3   0.71    14;...
0.850   0.150   1.5 3   0.71    28;0.850    0.150   1.5 3   0.71    56;...
0.835   0.165   1.5 3   0.72    7;0.835 0.165   1.5 3   0.72    14;...
0.835   0.165   1.5 3   0.72    28;0.835    0.165   1.5 3   0.72    56;...
0.820   0.180   1.5 3   0.73    7;0.820 0.180   1.5 3   0.73    14;...
0.820   0.180   1.5 3   0.73    28;0.820    0.180   1.5 3   0.73    56;...
0.805   0.195   1.5 3   0.75    7;0.805 0.195   1.5 3   0.75    14;...
0.805   0.195   1.5 3   0.75    28;0.805    0.195   1.5 3   0.75    56;...
0.790   0.210   1.5 3   0.76    7;0.790 0.210   1.5 3   0.76    14;...
0.790   0.210   1.5 3   0.76    28;0.790    0.210   1.5 3   0.76    56;...
0.775   0.225   1.5 3   0.77    7;0.775 0.225   1.5 3   0.77    14;...
```

```
0.775	0.225	1.5 3	0.77	28;0.775	0.225	1.5 3	0.77	56;...
0.760	0.240	1.5 3	0.79	7;0.760 0.240	1.5 3	0.79	14;...
0.760	0.240	1.5 3	0.79	28;0.760	0.240	1.5 3	0.79	56;...
0.745	0.255	1.5 3	0.81	7;0.745 0.255	1.5 3	0.81	14;...
0.745	0.255	1.5 3	0.81	28;0.745	0.255	1.5 3	0.81	56;...
0.730	0.270	1.5 3	0.82	7;0.730 0.270	1.5 3	0.82	14;...
0.730	0.270	1.5 3	0.82	28;0.730	0.270	1.5 3	0.82	56;...
0.715	0.285	1.5 3	0.84	7;0.715 0.285	1.5 3	0.84	14;...
0.715	0.285	1.5 3	0.84	28;0.715	0.285	1.5 3	0.84	56;...
0.700	0.300	1.5 3	0.86	7;0.700 0.300	1.5 3	0.86	14;...
0.700	0.300	1.5 3	0.86	28;0.700	0.300	1.5 3	0.86	56;...
0.685	0.315	1.5 3	0.88	7;0.685 0.315	1.5 3	0.88	14;...
0.685	0.315	1.5 3	0.88	28;0.685	0.315	1.5 3	0.88	56;...
0.670	0.330	1.5 3	0.90	7;0.670 0.330	1.5 3	0.90	14;...
0.670	0.330	1.5 3	0.90	28;0.670	0.330	1.5 3	0.90	56;...
0.655	0.345	1.5 3	0.92	7;0.655 0.345	1.5 3	0.92	14;...
0.655	0.345	1.5 3	0.92	28;0.655	0.345	1.5 3	0.92	56;...
0.640	0.360	1.5 3	0.94	7;0.640 0.360	1.5 3	0.94	14;...
0.640	0.360	1.5 3	0.94	28;0.640	0.360	1.5 3	0.94	56;...
0.625	0.375	1.5 3	0.96	7;0.625 0.375	1.5 3	0.96	14;...
0.625	0.375	1.5 3	0.96	28;0.625	0.375	1.5 3	0.96	56;...
0.610	0.390	1.5 3	0.98	7;0.610 0.390	1.5 3	0.98	14;...
0.610	0.390	1.5 3	0.98	28;0.610	0.390	1.5 3	0.98	56;...
0.595	0.405	1.5 3	1.01	7;0.610 0.390	1.5 3	0.98	14;...
0.595	0.405	1.5 3	1.01	28;0.595	0.405	1.5 3	1.01	56;...
0.580	0.420	1.5 3	1.03	7;0.580 0.420	1.5 3	1.03	14;...
0.580	0.420	1.5 3	1.03	28;0.580	0.420	1.5 3	1.03	56;...
0.565	0.435	1.5 3	1.06	7;0.565 0.435	1.5 3	1.06	14;...
0.565	0.435	1.5 3	1.06	28;0.565	0.435	1.5 3	1.06	56;...
0.550	0.450	1.5 3	1.09	7;0.550 0.450	1.5 3	1.09	14;...
0.550	0.450	1.5 3	1.09	28;0.550	0.450	1.5 3	1.09	56;...
0.535	0.465	1.5 3	1.12	7;0.535 0.465	1.5 3	1.12	14;...
0.535	0.465	1.5 3	1.12	28;0.535	0.465	1.5 3	1.12	56;...
0.520	0.480	1.5 3	1.15	7;0.520 0.480	1.5 3	1.15	14;...
0.520	0.480	1.5 3	1.15	28;0.520	0.480	1.5 3	1.15	56;...
0.505	0.495	1.5 3	1.19	7;0.505 0.495	1.5 3	1.19	14;...
0.505	0.495	1.5 3	1.19	28;0.505	0.495	1.5 3	1.19	56;...
0.490	0.510	1.5 3	1.22	7;0.490 0.510	1.5 3	1.22	14;...
0.490	0.510	1.5 3	1.22	28;0.490	0.510	1.5 3	1.22	56;...
0.475	0.525	1.5 3	1.26	7;0.475 0.525	1.5 3	1.26	14;...
0.475	0.525	1.5 3	1.26	28;0.475	0.525	1.5 3	1.26	56;...
0.460	0.540	1.5 3	1.30	7;0.460 0.540	1.5 3	1.30	14;...
0.460	0.540	1.5 3	1.30	28;0.460	0.540	1.5 3	1.30	56;...
0.445	0.555	1.5 3	1.35	7;0.445 0.555	1.5 3	1.35	14;...
0.445	0.555	1.5 3	1.35	28;0.445	0.555	1.5 3	1.35	56;...
0.430	0.570	1.5 3	1.40	7;0.430 0.570	1.5 3	1.40	14;...
0.430	0.570	1.5 3	1.40	28;0.430	0.570	1.5 3	1.40	56;...
0.415	0.585	1.5 3	1.45	7;0.415 0.585	1.5 3	1.45	14;...
0.415	0.585	1.5 3	1.45	28;0.415	0.585	1.5 3	1.45	56;...
0.400	0.600	1.5 3	1.50	7;0.400 0.600	1.5 3	1.50	14;...
0.400	0.600	1.5 3	1.50	28;0.400	0.600	1.5 3	1.50	56;...
0.385	0.615	1.5 3	1.56	7;0.385 0.615	1.5 3	1.56	14;...
0.385	0.615	1.5 3	1.56	28;0.385	0.615	1.5 3	1.56	56;...
0.370	0.630	1.5 3	1.62	7;0.370 0.630	1.5 3	1.62	14;...
0.370	0.630	1.5 3	1.62	28;0.370	0.630	1.5 3	1.62	56;...
0.355	0.645	1.5 3	1.69	7;0.355 0.645	1.5 3	1.69	14;...
0.355	0.645	1.5 3	1.69	28;0.355	0.645	1.5 3	1.69	56;...
0.340	0.660	1.5 3	1.77	7;0.340 0.660	1.5 3	1.77	14;...
0.340	0.660	1.5 3	1.77	28;0.340	0.660	1.5 3	1.77	56;...
0.325	0.675	1.5 3	1.85	7;0.325 0.675	1.5 3	1.85	14;...
0.325	0.675	1.5 3	1.85	28;0.325	0.675	1.5 3	1.85	56;...
```

```
0.310   0.690   1.5 3   1.94    7;0.310 0.690   1.5 3   1.94    14;...
0.310   0.690   1.5 3   1.94    28;0.310    0.690   1.5 3   1.94    56;...
0.295   0.705   1.5 3   2.03    7;0.295 0.705   1.5 3   2.03    14;...
0.295   0.705   1.5 3   2.03    28;0.295    0.705   1.5 3   2.03    56;...
0.280   0.720   1.5 3   2.14    7;0.280 0.720   1.5 3   2.14    14;...
0.280   0.720   1.5 3   2.14    28;0.280    0.720   1.5 3   2.14    56;...
0.265   0.735   1.5 3   2.26    7;0.265 0.735   1.5 3   2.26    14;...
0.265   0.735   1.5 3   2.26    28;0.265    0.735   1.5 3   2.26    56;...
0.250   0.750   1.5 3   2.40    7;0.250 0.750   1.5 3   2.40    14;...
0.250   0.750   1.5 3   2.40    28;0.250    0.750   1.5 3   2.40    56];


global inp;
global targs;

inp =inputs';
n =4
targs = NCPAcompressiveStrengthTargets';
compressiveStrengthNN = feedforwardnet(n);
compressiveStrengthNN = configure(compressiveStrengthNN, inp,targs);
compressiveStrengthNN.performParam.regularization = 0.01;
compressiveStrengthNN = train(compressiveStrengthNN,inp,targs);
X0 = getx(compressiveStrengthNN);
p = numel(X0);
% view(compressiveStrengthNN);
h = @(x) mse_test(x, compressiveStrengthNN, inp, targs);

%  ga_opts = gaoptimset('PopInitRange', [-1;1], 'TolFun', 1e-
10,'display','iter');
%  ga_opts = gaoptimset(ga_opts, 'StallGenLimit', 100, 'FitnessLimit', 1e-
5, 'Generations', 100);;
ga_opts = gaoptimset('TolFun', 1e-8,'display','iter');
[x, err_ga] = ga(h, p, ga_opts)
 optimisedNN = setwb(compressiveStrengthNN, x');
 optimisedNN = train(optimisedNN, inp, targs);


% --------------------------------------------------------------------
function Train_Callback(hObject, eventdata, handles)
global inp;
global targs;
global compressiveStrengthNN;
compressiveStrengthNN = train(compressiveStrenghtNN,inp,targs);
view(compressiveStrengthNN);


% --------------------------------------------------------------------
function exit_Callback(hObject, eventdata, handles)
close;


% --------------------------------------------------------------------
function viewStrucure_Callback(hObject, eventdata, handles)
global compressiveStrengthNN;
view(compressiveStrengthNN);
```

APPENDIX K: Various stages in the processing and production of nanosized cassava peel ash

APPENDIX L: Various stages in production of NCPA-concrete