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Optimization of Mechanical Properties of Concrete made with Bambara nut shell ash and Quarry dust using Artificial Neural Network

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Abstract
The optimal utilization of valuable resources like money and time through the adoption of artificial neural network (ANN) and its ability to give reliable solutions to problems that are challenging to conventional statistical models, has increased the interest of scholars in using it to estimate concrete properties. In this study, ANN is employed to optimize the compressive and flexural strength of concrete containing Bambara nutshell ash (BNSA) and quarry dust (QD) as partial replacement of cement and sand respectively. This replacement was done at 0 – 50% using 2.5% interval with 1:2:4 mix proportion for 14, 21, 28 and 56 curing days. Two hundred and fifty-two (252) concrete cubes and beam moulds were produced with QD and BNSA. The optimum values were obtained at 22.5% replacement and mix ratio of 0.775: 0.225: 1.55: 0.45: 4. The optimum values of compressive strength recorded from experimental works at 14, 21, 28 and 56 curing age were 24.29 N/mm^2, 24.78 N/mm^2, 25.14 N/mm^2, and 27.36 N/mm^2 respectively. Optimum values for the flexural strength were 8.89 N/mm^2, 9.32 N/mm^2, 9.41 N/mm^2 and 13.21 N/mm^2. The ANN model had 6 neurons, 10 neurons, and 2 neurons in the input, hidden and output layers respectively. A total of ninety (90) training data set were introduced to the model. 45 samples were used for training, 23 samples each were used for testing and validation. The modelled results were very close to the experimental outcome. 20% replacement was concluded as optimum for structural concrete. The model's adequacy was further tested using the Student's T test. The calculated T-value (-2.74 and -3.45) for the compressive and flexural strength of BNSA-QD-concrete were less than that from the T-table (2.09) at 95% confidence level, certifying that the network predictions are suitable and reliable for prediction and optimization of BNSA-QD concrete. The adoption of ANN significantly offers the elbow room for modification during concrete production and attaining required strength. The use of bambara nutshell ash and quarry dust in concrete making are recommended as they improve concrete properties and curtails the issue of poor waste management by transmuting it into wealth

Keywords: Concrete, Bambara nutshell ash (BNSA), Quarry dust (QD), Artificial neural network (ANN), Optimization.

1. Introduction

Infrastructural advancement and engineering practices of both developing and developed nations largely depends on the use of concrete. Concrete has gained more attention as the dominant construction material due to the availability of its constituents, its eco-commercial advantages and its ability to be tailored into desired specifications in a distinct manner (Ayuba et al., 2022; Nwa-David, 2023a). Concrete in its fundamental structure is the blend of cement, water and aggregates. Concrete production places more demand for cement due to its binding role. The depletion of limestone deposits, discharge of toxic metals, noise pollution, emission of carbon dioxide which has contributed to global warming and high cost of cement production, has prompted the development of supplementary cementitious materials (SCMs) that would partially or totally replace ordinary and conventional cements (Olafusi et al., 2019; Nwa-David et al., 2023a; Oyebisi et al., 2019).

Uncontrolled sand mining has contributed to environmental degradation. Due to the strict regulations placed on river sand mining by government agencies, there is scarcity and an increase in the cost of quality river sand for concrete production and a search for alternatives to replace sand, either partially or wholly. One of such alternatives is quarry dust. Quarry dust is a residual of the rock quarrying process sufficiently available and minimally utilized in quarry sites.

Agricultural and industrial wastes that are often disposed in landfills or burnt openly polluting the atmosphere, has gained great attention and usefulness in the construction industry because their powder or ash such as cassava peel ash, oyster shell ash, periwinkle shell ash, sawdust ash, bone powder ash, rice husk ash, bambara nut shell ash and bagasse ash are adopted as SCMs (Rukzon and Chindaprasirt, 2012; Ayuba et al., 2022; Nwa-David and Ibearugbulem 2023; Nwa-David, 2023b; Eze et al., 2022). This study adopts bambara nut shell ash for its investigation. Bambara nut shells are by-products obtained during the processing of Bambara seeds into flour for human consumption and they are the major agro-waste in Africa (Eze et al., 2022). The shell is generated after splitting the seeds in an attrition mill to remove the shells, winnowing to remove loosened testa (Sutivisedsak et al., 2012). Bambara nutshell ash (BNSA) is produced after burning the sun-dried shell to a certain temperature in a kiln. Investigating the strength property of concrete adopting the conventional materials and methods of mix design., is a difficult, costly and time-consuming task due to the absence of defined formulations of its constituent materials and variations in concrete mixing occasioned by qualitative-knowledge-based technique. The non-linear relationship between concrete properties and its ingredients as well as the necessity of achieving a reliable and accurate prediction of concrete behaviour; is a gap worth filling through this study.

To avert material loss and unnecessary test repetition, model development for concrete strength prediction has become a regular practice among scholars. Soft computing techniques such as artificial neural network (ANN) has gained more attention than statistical models due to the ease, speed of predictions and ability to obtain the optimum material combination to balance cost and strength. ANN is a computational model that behaves like the biological neural networks. ANN comprises of three major sections known as the input, hidden and output layers. By a learning process, ANN is designed for a peculiar application such as pattern recognition or data classification (Nwa-David et al., 2023b; Nwobi-Okoye et al., 2013; Russell and Norvig, 2003). ANN's usefulness in performing a variety of tasks is due to its ability to learn quickly. To ensure acceptable prediction accuracy with respect to flexural and compressive strength, ANN is employed in this study.

Optimization of concrete properties using artificial neural network is common among researchers. Artificial neural network (ANN) was employed by Alaneme and Mbadike (2019) as the modelling tool for evaluating properties of concrete whose cement ratio was partially replaced by fractions of aluminum waste and sawdust ash. The authors adopted a two-layer feed-forward network, hidden neurons with sigmoid activation function and linear output neurons for the simulation of the model. Their model predicted the setting time and concrete compressive strength at different curing days and the model performance was evaluated using linear regression, RMSE and R-values. Flexural strength was not considered in their study. Percentage error and student's T-test was not used for evaluation of model performance. BNSA was also not adopted in their study.

Alaneme and Mbadike (2021), replaced cement with BNSA from 0-40%. The authors carried out test on the concrete's compressive strength, density, Poisson ratio, and young's modulus of elasticity. They employed a mix proportion of 1:3:6 with water cement ratio of 0.55 and cured for 3, 7, 28, 60 and 90 days. The authors did not employ artificial neural network in their study. The authors did not consider flexural strength. Oti et al. (2019) developed an ANN-model to predict the compressive strength of BNSA concrete. A genetic algorithm was employed to optimize the mix proportions by considering BNSA content, water-to-cement ratio, and curing time. Their study demonstrated that the proposed approach could effectively optimize BNSA concrete for enhanced compressive strength. The flexural strength of the concrete was not examined. Kosti´c and Vasovi´c (2015) formulated an ANN-model for estimating compressive strength of concrete. The authors employed different water-to-cement ratios using 75 samples with their compressive strength being determined at 7, 20 and 32 curing days. The water/cement ratio, curing periods, and number of freeze/thaw cycles were used in the input-layer.

Ogbodo & Dumde (2017) adopted a 3-layered feed-forward neural network model with a back-propagation algorithm to predict concrete mix ratio. The model performed quite well in predicting, not only the output parameters used in the training process, but also those of test mixtures that were unfamiliar to the neural network. Their study captured the utility, reliability and usefulness of ANN.

Awodiji *et.al.,* (2018) determined experimentally the compressive strength of hydrated lime-cement concrete without the inclusion of any pozzolanic material using some selected mix ratios and developed an ANN-model that can be used to predict the compressive strength of the concrete. Their study showed that the concrete can be used as a structural concrete if the cement replacement was not up to 30%. The network results were in conformity with the experimental outcome. The Student's T test value proved the reliability of the network prediction. However, the authors did not employ BNSA neither was quarry dust considered in their concrete mix.

Abdulla (2020) employed ANN to formulate an empirical relationship for predicting the axial compression capacity and axial strain of concrete-filled plastic tubular specimens. The author employed 72 experimental test data of the specimens and unconfined concrete for training, testing, and validating the model. Suescum-Morales *et al.,* (2021) developed a novel ANN-model to predict the 28-day compressive strength of recycled aggregate concrete. The authors used 11 neurons in the input layer. Levenberg–Marquardt (LM) and Bayesian Regularization (BR) were adopted as the two training techniques for the ANN combining 15 and 20 hidden layers. There was no consideration for quarry dust. The cement content was not partially replaced with any material. The authors did not consider the flexural-strength of the concrete. Nwa-David *et al.,* (2023b) modelled the compressive strength of concrete containing nanostructured cassava peel ash adopting ANN. The authors presented 240 data set to the network, used 60 for validation and 60 for performance testing. Their network architecture was 6-10-1. The authors employed student's T-test and percentage error method for validation of the model. BNSA was not taken into account in their study and flexural strength was not evaluated.

The idea of optimization and the adoption of soft computing techniques for it, is rare in literatures and this gap has necessitated the research. The usefulness of ANN in prediction of concrete properties cannot be overemphasized. However, more works need to be done for concealed areas. The distinctiveness of this study lies in its input and output architecture. Unlike previous studies, this study considered two output variables: compressive strength and flexural strength. The content of its input layer is also such that was not addressed by preceding works. The ANN architecture of this study is a gap worth filling. Antecedent authors generated their data from existing literatures. The peculiarity of this work is that the data introduced to the network were all derived from the laboratory experiments. The accuracy and reliability of the model formulated in this study distinguishes it. Many SCMs have been considered by different previous authors but very few studies have done on the use of bambara nutshell ash in concrete and this gap is addressed in this work. The peculiarity of this work is also seen in its curing ages and interval of percentage replacement. Their variation enhances thorough investigation and modelling. The objective of this study is to investigate the effects of BNSA and quarry dust on the fresh and hardened properties of concrete and to optimize these properties using ANN.

2.0 Material and methods

2.1 Materials

The *Dangote* brand of Ordinary Portland Cement that conformed to the requirements of BS12 (1996) was used. Bambara nut shell was obtained from Umunevo and Onuato villages in Enugu North, Enugu State, Nigeria. These nuts were frequently used by the villagers to produce what is locally called okpa in Igbo, epa-roro in Yoruba and kwaruru in Hausa. The shells that were removed from the nuts were dried under the sun and burnt at a temperature of about 620 °C in a kiln. After burning, the ash was collected and sieved in the laboratory with 150/μm sieve size to obtain a finely divided material which were taken for the practical.

The sand was sourced from Imo River, Imo State of Nigeria. It was sieved through 10mm British Standard test sieve to remove cobbles to conform to the requirements of BS 882 (1992). The granite 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) The test Quarry dust material utilized as admixture in the experimental investigation was obtained from Crushed Rock quarry site, Lokpanta, Abia State, Nigeria. The required quantity of QD samples were gotten which was sundried, stored and prepared for experimentation. The water used was obtained from borehole. The water was clean and free from any visible impurities. it conformed to the requirements of BS 3140 (1980).

2.2 Methods

2.2.1 Experimental Method

Preliminary tests were carried out on the constituent materials so as to determine their suitability for production of concrete. The binder and fine aggregate were partially replaced with Bambara nutshell ash (BNSA) and quarry dust (QD) respectively. The replacements were done at 2.5 % intervals, from 0 % to 50 %. Concrete mix ratio of 1: 2: 4 and water-cement ratio of 0.55 were used for the concrete making. BNSA and QD were first blended homogeneously with OPC and sand respectively, with water and the coarse aggregate at the required proportion. The homogeneous mixture was then laid into the 150mm x 150mm x 150mm concrete cubes and was demoulded after 24hours. A total of two hundred and fifty-two (252) concrete cubes and beam moulds were produced with QD and BNSA using varied percentage replacement at 2.5% intervals. Replicates of three cubes, were cast for each percentage replacement. The cubes were cured by immersion in a curing tank and was crushed after 14, 21, 28 and 56 days to investigate their compressive strength. 100mm × 100mm × 400mm beam moulds were used for flexural strength test.

2.2.2 ANN Modeling

The experimental outcome was presented to the MATLAB computational system for ANN model prediction. The network comprises of the input layer, the hidden layer and the output layer. The input layer consists of four (4) variables and they are; cement, BNSA, aggregates and quarry dust. There are ten (10) neurons in the hidden area. There are two outputs; the compressive and flexural strengths. The optimized network architecture is 4-10-2 as shown in the Figure 1 below. This architecture was chosen to make the modelling faster, accurate and efficient as it identified only the major input data. Tansig and purelin were the activation functions adopted in the model in order to capture the exact non-linear relationship between the inputs and to assist in transforming the input into the two desired output.

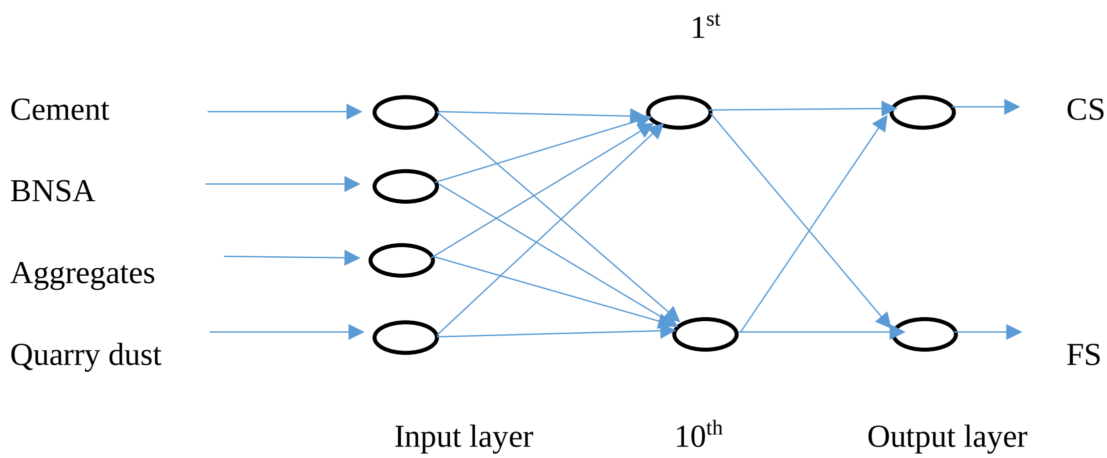

Figure 1. ANN Architecture

Fifty percent of the total training data were employed for training while twenty-five percent each were used for validation and testing. A total of ninety (90) training data set were introduced to the network. 45 samples were used for training, 23 samples each were used for testing and validation. To satisfy the MSE (Mean square error) criteria, the process was repeated based on trial and error. Training implies feeding sorted data sets with initialized variables and the network is adjusted according to error function. Validation is the evaluation of the network generalization performance and to halt training when generalization stops improving. Testing provides performance during and after training. The experimental results were compared with the modelled results and the ANN model was validated using Students' t-test.

3.0 Results and Discussions

3.1. Chemical analysis of portland cement, quarry dust and BNSA

The chemical composition of the constituent materials used in this work are as shown Table 1. The chemical and physical properties of the admixtures consisting of Bambara nut shell ash (BNSA) and quarry dust (QD), and Portland cement used in the laboratory methods were presented Table 1. The derived physicochemical characteristics obtained from X-ray fluorescence (XRF) test indicate that BNSA has 54.58% SiO_2, 16.8% Al_2O_3 and 8.46% Fe_2O_3 to obtain a sum of 79.84% which signifies good pozzolanic characteristics as a Supplementary Cementitious Materials (SCM) in accordance with ASTM C 618, 98 specifications. The abundance of CaO, Al_2O_3 and Fe_2O_3 at 11.3%, 20.6% and 6.405% respectively in the test Portland cement helps to enhance complete cement hydration which improves durability and mechanical strength behavior of the produced green concrete. Chemical analysis of QD indicates high alumino-silica content with 62.44% SiO_2 and 18.73% Al_2O_3, 4.81% of CaO and 3.15 of K_2O. The mechanism is that the silicates and aluminates obtained from the admixture react with calcium hydroxide during cement-additives hydration reaction to derive hydration products which form hard mass with time. The low LOI of BNSA and QD (3.45 and 0.48) implies that it has high reactivity when blended in concrete and this enhances strength. Sulphur trioxide ($S0_3$) which is 1.41% for BNSA and a trace for QD is below 4% maximum recommended by ASTM C618 (2012). This shows that the concrete made with these materials will have improved strength.

Table 1. Physicochemical Properties of Admixtures and Cement

Chemical Analysis Results			
Elemental Oxide	**BNSA (%)**	**Cement (%)**	**QD (%)**
CaO	10.16	11.3	4.81
MgO	0.5	0.093	2.59
Fe_2O_3	8.46	6.405	6.58
Na_2O	0.36	2.1	Nil
Al_2O_3	16.8	20.6	18.73
SiO_2	54.58	52.4	62.44
ZnO	0.72	Trace	0.102
MnO	2.56	Trace	Trace
LOI	3.45	3.9	0.48
SO_3	1.41	Trace	Trace
CUO	1	Trace	0.12
TiO_2	Trace	0.52	1.22
K_2O	Trace	2.6	3.15

3.2 Physical properties of constituent materials

The result of particle size distribution of the aggregates, is as shown in Tables 2 and 3. The river sand is uniformly graded because it has coefficient of uniformity and coefficient of curvature values of 2.23 and 1.11 respectively obtained from Table 2; as D_{10}, D_{30} and D_{60} were 0.26, 0.41, and 0.58 respectively. The coarse aggregate has coefficient of uniformity and coefficient of curvature values of 1.94 and 1.39 respectively obtained from Table 3; D_{10}, D_{30} and D_{60} were 9.46, 15.58, and 18.40 respectively. Its coefficient of uniformity and curvature values indicate a poorly graded particle. The result of specific gravity test for the fine aggregate, coarse aggregate, portland cement and BNSA were 2.76, 2.65, 3.09 and 2.30 respectively. The BNSA has a lower specific gravity when compared with the specific gravity of cement. This implies that partially replacing OPC with BNSA will result to reduced weight of concrete members. BNSA is 1.4 times lighter than cement. Consequently, concrete incorporating BNSA was lighter in weight than the concrete without BNSA.

Table 2. Particle size distribution of river sand

Sieve size (mm)	**Mass of sand passing (g)**	**Mass of sand retained (g)**	**% passing**
4.75	550	0	100
2.36	504.5	45.50	91.73
1.18	438.69	65.81	79.76
0.850	380.05	58.64	69.10
0.6	335.27	44.78	60.96
0.425	195.28	139.99	35.51
0.3	97.03	98.25	17.65

0.212	40.85	56.18	7.44
0.15	12.99	27.86	2.37
0.075	0	12.99	0
Total		550	

Table 3. Particle size distribution of granite chippings

Sieve size (mm)	**Mass of granite passing (g)**	**Mass of granite retained (g)**	**% passing**
31.5	2200	0	100
22.4	2118.78	81.22	96.31
19	1675.83	442.95	76.18
16	697.87	977.96	31.73
12.5	403.72	294.15	18.36
9.5	254.21	149.51	11.56
6.3	47.41	206.80	2.16
4.75	14.74	32.67	0.67
Pan	0	14.74	0
Total		2200	

3.3 Properties of fresh and hardened concrete

The values obtained from the slump test correspond to the designed slump range of 30– 60mm. It is observed from Figure 1, that the workability increased with increase in replacement of cement with BNSA and replacement of sand with quarry dust. This is attributable to increase in surface area and filler effect of BNSA inclusion in the concrete matrix. The inclusion of BNSA in the concrete matrix increased the initial and final setting times from 0 to 50% replacement intervals as shown in Figure 2. This led to retardation in the hydration process. Hence the concrete is not susceptible to the problem of false set.

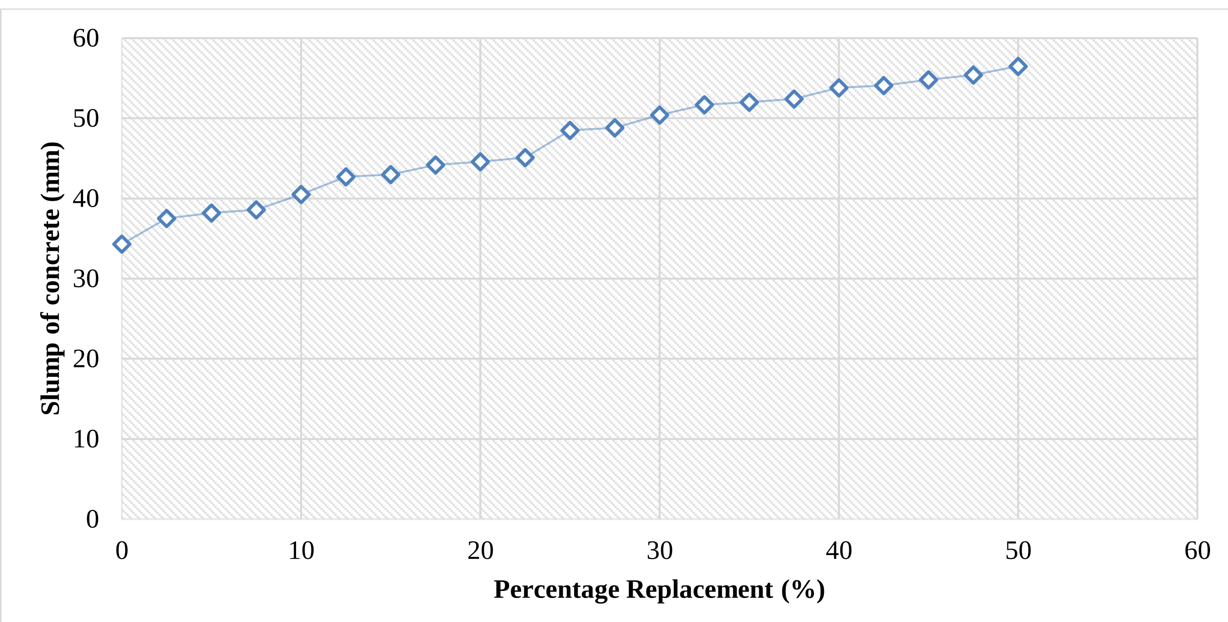

Figure 1. Workability of QD-BNSA Concrete

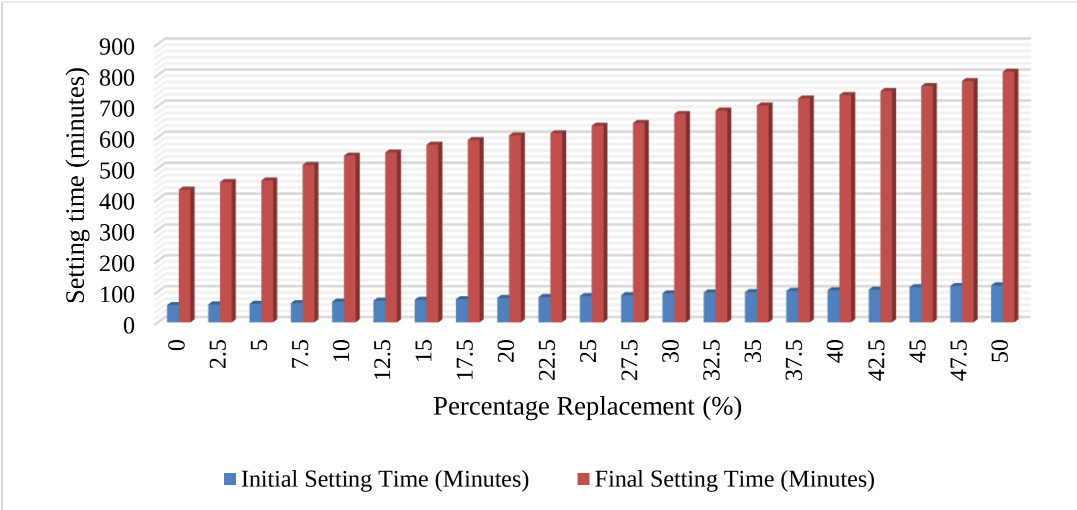

Figure 2. Setting time of QD-BNSA-concrete

The outcome of the compressive strength obtained from different QD-BNSA-concrete mixes at various curing age used for this study is shown in Figure 3. The strength increases with the age of curing at both 14, 21, 28 and 56 days curing while it decreases with increase in the BNSA-QD contents beyond 23% replacement. Previous studies did not consider beyond 28 days. It was observed that prolonged curing makes room for more moisture for hydration and strength development. Due to the pozzolanic reaction between $Ca(OH)_2$ from cement hydration with the SiO_2 of BNSA, strength increased as curing period increased. The experimental optimum compressive strength of 24.29 N/mm^2, 24.78 N/mm^2, 25.14 N/mm^2 and 27.36 N/mm^2 was achieved at 22.5% replacement and mix ratio of 0.775: 0.225: 1.55: 0.45: 4, at 14, 21, 28, and 56 days of age respectively. The percentage difference between this optimum values and control (0% replacement) values are 10.2%, 5.4%, 2%, and 0.3 % respectively.

From Figure 4, it was observed that flexural strengths reduced with increase in quarry dust content. As the curing age increased, the flexural strength increased. This increment is traceable to the bonding and filler effect of BNSA in the composite. However, beyond 22.5%, the concrete may not be suitable for resisting high bending stresses. The optimum blend was obtained at a mix ratio of 0.775: 0.225: 1.55: 0.45: 4.

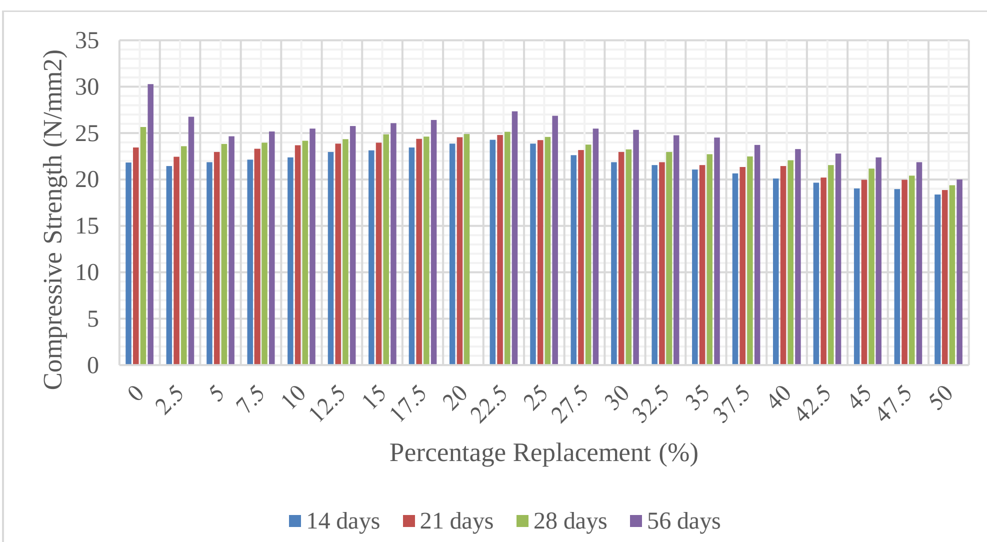

Figure 3. Compressive strength of BNSA-QD Concrete at different percentage replacements.

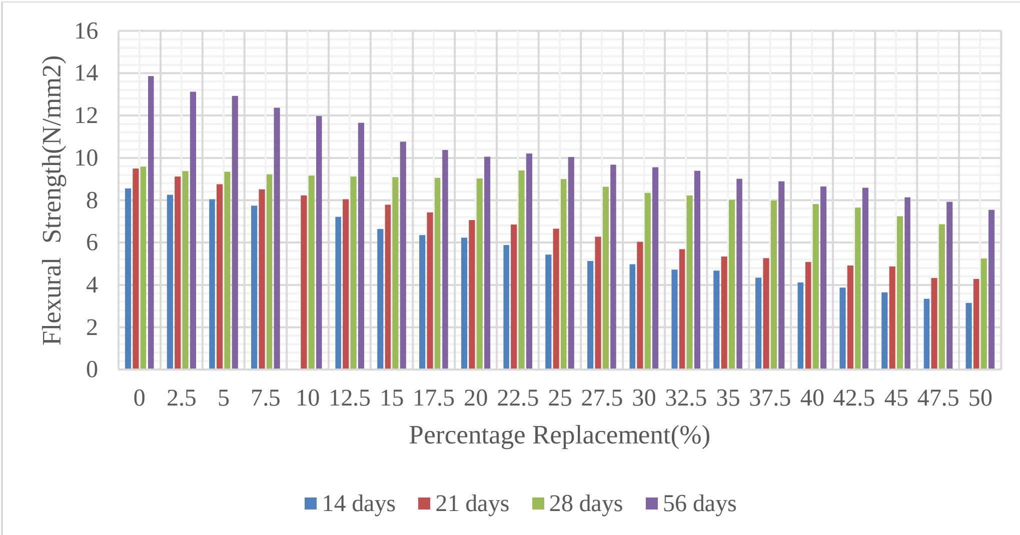

Figure 4. Flexural strength of BNSA-QD Concrete at different percentage replacements.

3.4 ANN Model

The designed framework for ANN model development consists of six input variables (cement, BNSA, fine aggregate, QD fractions, coarse aggregate and curing periods) and two output (compressive and flexural strength) variables. In order to derive the optimized network, the training data were used to generate the initialized connection weights of the neural network with varying number of hidden layer. With respect to the optimized mix ratio of the concrete, the model is faster in estimating the strength behaviour of the concrete to a certain degree of precision and this will assist the mix-design personnel to make reliable decisions, circumventing the multiple trials with varied mix proportions. The plot in Figure 5 indicates that the best performance was derived at 11 Epochs with mu of 0.001. After 6 validation checks, a gradient of 0.018226 was achieved. The best validation check occurred at the 5th epoch at a mean square error of 10-2 and best performance at 0.19519. After epoch 5, the errors re-occurred and the test was terminated at epoch 11. Epoch 5 served as the base and its weights were taken as the final weights.

Figure 6 showed that the best performance of 0.1952 occurred at epoch 5 and ended at epoch 11. The plot displayed the training, validation and test. The mean square error and validation performance of the model started at a high value and decreased to a little value. The result indicated satisfactory model performance with the smart model capable of predicting the target output parameters accurately generalizing the sets of complex input variables with minimum error. From the graph presented in Figure 7, the total error range was divided into 20 smaller bins. It was observed that the 7th bin had zero error at 0.07763 which produced the best performance for the network. The corresponding point of zero error is not located at the mid of the plot with 25, 30 and 35 instances for training, validation and testing respectively.

The statistical computation results obtained show satisfactory performance in terms of prediction accuracy of the ANN model with 0.99909, 0.99717 and 0.99846 results obtained for training, testing and validation respectively. In Figure 8, three plots which represent training, validation and testing datasets were presented while the dashed line in the plots represent the regression line at which error is zero. The R-values were very close to 1, which confirms the excellency of the ANN model. The R-values obtained herein shows some similarities with the studies of Nwa-David *et al.*, (2023b), Awodiji *et al.*, (2018), Ogbodo and Dumde (2017).

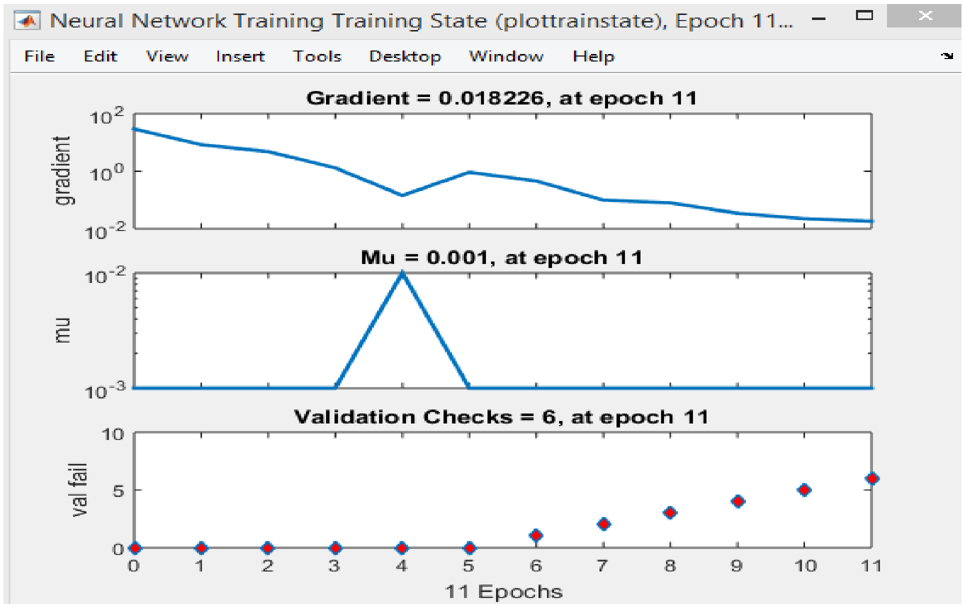

Figure 5. Training state of the network

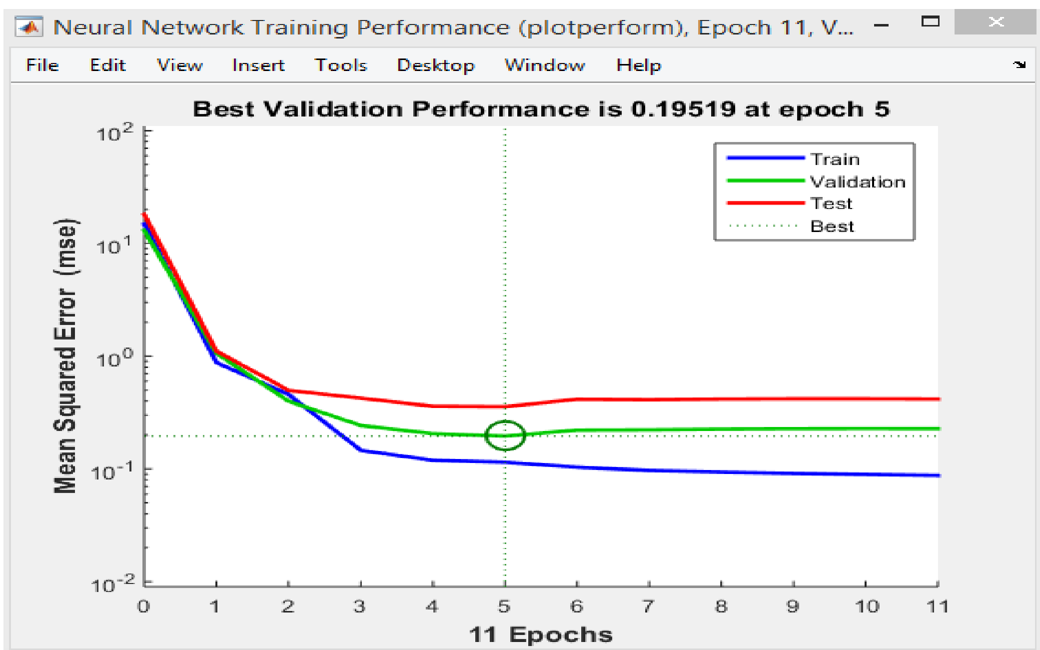

Figure 6. ANN best validation performance

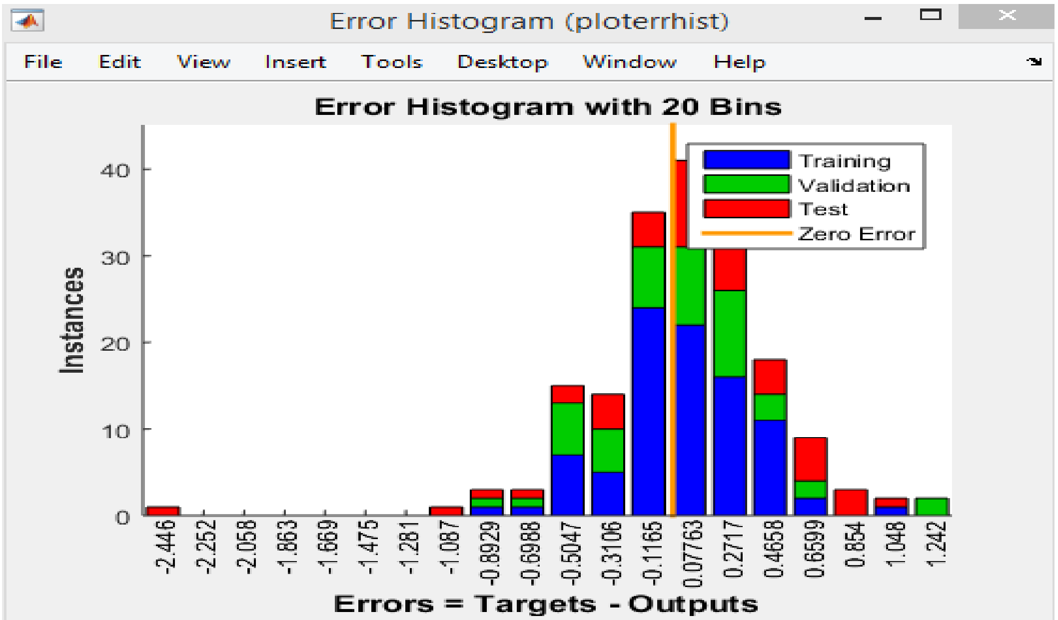

Figure 7. ANN Error Histogram

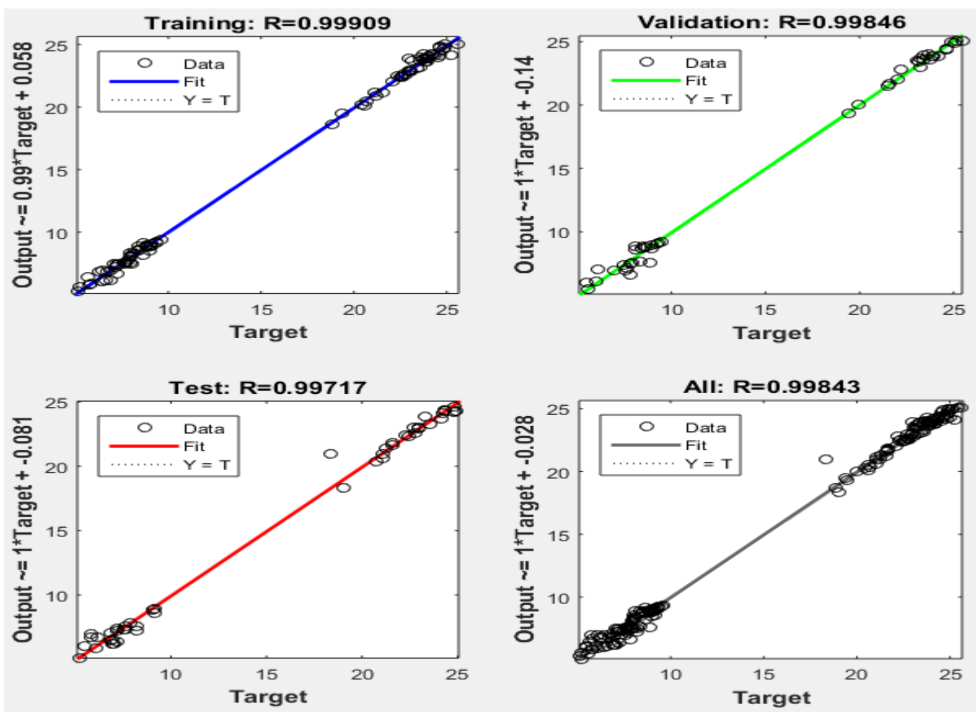

Figure 8. Regression plot

3.5 Model Validation

The validation of developed smart intelligent model is necessary to evaluate the performance of the model in respect to prediction accuracy. To achieve this, the results derived from ANN model and experimental results are compared statistically using percentage error method and Student's t-test. These methods were preferred because the sample size is small and with the intent of accurately providing scientific proof that the model is reliable and consistent before it can be adopted in routine analysis of structural elements. The experimental results were compared with neural network prediction of the compressive strength of concrete containing BNSA and QD using percentage error method, as shown in Table 4. These strength values corresponded to concrete specimens Z_1, Z_2, Z_3, Z_4, Z_5 for the 14 days, 21 days, 28days and 56 days' strength at 0%, 5%, 10%, 15% and 20% BNSA replacement respectively. A two-tailed Student's t- test was carried out and the computations presented in Table 5 and Table 6 for compressive and flexural strength test respectively. It can be seen from Table 4, that the highest percentage error obtained was 2.45%, which was not up to 10%. This result further confirms that the neural network has been satisfactorily trained, as all outputs given by the network, are close to the values of the experimental results.

Table 4. Comparison of Experimental Results against Neural Network Prediction for the Compressive Strength of BNSA Concrete using Percentage Error Method.

Mix Label	Curing Age	Experimental Results (N/mm^2)	ANN Prediction (N/mm^2)	Error	% Error
Z_1	14	21.82	22.424	-0.604	-2.69354
Z_2	14	21.87	21.347	0.523	2.449993
Z_3	14	22.38	23.328	-0.948	-4.06379
Z_4	14	23.14	23.120	0.020	0.086505
Z_5	14	23.85	24.773	-0.923	-3.72583
Z_1	21	23.45	25.204	-1.754	-6.95921
Z_2	21	22.95	22.534	0.416	1.846099
Z_3	21	23.69	24.321	-0.631	-2.59447
Z_4	21	23.98	24.218	-0.238	-0.98274
Z_5	21	24.55	24.390	0.160	0.656007
Z_1	28	25.64	26.229	-0.589	-2.24561
Z_2	28	23.82	23.739	0.081	0.341211
Z_3	28	24.18	24.538	-0.358	-1.45896
Z_4	28	24.86	24.902	-0.042	-0.16866
Z_5	28	24.91	25.205	-0.295	-1.1704
Z_1	56	27.28	28.112	-0.832	-2.95959
Z_2	56	24.67	25.241	-0.571	-2.26219
Z_3	56	25.48	25.781	-0.301	-1.16753
Z_4	56	26.08	26.345	-0.265	-1.00588
Z_5	56	26.64	26.238	0.402	1.532129

Table 5. Statistical student's T-test for ANN model validation for compressive strength of BNSA-QD Concrete

S/No.	E_x (N/mm^2)	N_p (N/mm^2)	D_i=E_x-N_p	D_A=($\sum D_i$)/N	D_A-D_i	$(D_A-D_i)^2$
1	21.82	22.424	-0.604	-0.33745	0.26655	0.071049
2	21.87	21.347	0.523	-0.33745	-0.86045	0.740374
3	22.38	23.328	-0.948	-0.33745	0.61055	0.372771
4	23.14	23.120	0.020	-0.33745	-0.35745	0.127771
5	23.85	24.773	-0.923	-0.33745	0.58555	0.342869
6	23.45	25.204	-1.754	-0.33745	1.41655	2.006614
7	22.95	22.534	0.416	-0.33745	-0.75345	0.567687
8	23.69	24.321	-0.631	-0.33745	0.29355	0.086172
9	23.98	24.218	-0.238	-0.33745	-0.09945	0.00989
10	24.55	24.390	0.160	-0.33745	-0.49745	0.247457
11	25.64	26.229	-0.589	-0.33745	0.25155	0.063277
12	23.82	23.739	0.081	-0.33745	-0.41845	0.1751
13	24.18	24.538	-0.358	-0.33745	0.02055	0.000422
14	24.86	24.902	-0.042	-0.33745	-0.29545	0.087291
15	24.91	25.205	-0.295	-0.33745	-0.04245	0.001802
16	27.28	28.112	-0.832	-0.33745	0.49455	0.24458
17	24.67	25.241	-0.571	-0.33745	0.23355	0.054546
18	25.48	25.781	-0.301	-0.33745	-0.03645	0.001329
19	26.08	26.345	-0.265	-0.33745	-0.07245	0.005249
20	26.64	26.238	0.402	-0.33745	-0.73945	0.546786

Where;
Ex = Experimental responses.
Np=Neural network model responses.
N = the Number of Responses = 20.
∑Di= -6.749
∑ (DA -Di)^2 = 5.753035
S^2 = [∑(DA -Di)^2]/(N-1) = 0.302791
s =√ S^2 = 0.550265
DA x √N = -1.50935
T = [DA x √N]/s = -2.74294
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 (0.05,19) = 2.09

Table 6. Statistical student's T-test for ANN model validation for flexural strength of BNSA-QD Concrete

S/No.	E_x (N/mm^2)	N_p (N/mm^2)	D_i=E_x-N_p	D_A=(∑D_i)/N	D_A-D_i	(D_A-D_i)^2
1	8.56	8.824	-0.264	-0.269	-0.005	0.000025
2	8.04	8.258	-0.218	-0.269	-0.051	0.002601
3	7.39	7.807	-0.417	-0.269	0.148	0.021904
4	6.64	6.985	-0.345	-0.269	0.076	0.005776
5	6.23	6.263	-0.033	-0.269	-0.236	0.055696
6	9.49	9.935	-0.445	-0.269	0.176	0.030976
7	8.76	8.457	0.303	-0.269	-0.572	0.327184
8	8.22	8.391	-0.171	-0.269	-0.098	0.009604
9	7.78	7.864	-0.084	-0.269	-0.185	0.034225
10	7.06	7.928	-0.868	-0.269	0.599	0.358801
11	9.58	10.759	-1.179	-0.269	0.910	0.828100
12	9.34	9.654	-0.314	-0.269	0.045	0.002025
13	9.17	9.320	-0.150	-0.269	-0.119	0.014161
14	9.09	9.342	-0.252	-0.269	-0.017	0.000289
15	9.02	9.751	-0.731	-0.269	0.462	0.213444
16	13.87	13.842	0.028	-0.269	-0.297	0.088209
17	12.92	13.272	-0.352	-0.269	0.083	0.006889
18	11.98	11.805	0.175	-0.269	-0.444	0.197136
19	10.76	10.761	-0.001	-0.269	-0.268	0.071824
20	10.05	10.112	-0.062	-0.269	-0.207	0.042849

Where;
Ex = Experimental responses.
Np=Neural network model responses.
N = the Number of Responses = 20.
∑D_i = -5.38
∑ (D_A -D_i)^2 = 2.311718
S^2 = [∑ (DA -Di)^2]/(N-1) = 0.121669
s =√ S^2 = 0.348811
DA x √N = -1.203
T = [DA x √N]/s = -3.44887
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 (0.05,19) = 2.09

The computed T-value from the ANN predicted results were -2.74 and -3.45 for compressive and flexural strength respectively; which are less than the standard T-value of 2.09 obtained from the standard statistical tables. This means there is no significant difference between the neural network model results and the experimental results. This test of adequacy further affirms that the result from the neural network model obtained herein are reliable and the model could be used to predict the compressive and flexural strength of BNSA-QD concrete at 95% confidence level. This means that the neural networks have been satisfactorily trained, as all the outputs given by the network, are close to the values of the experimental results.

4.0. Conclusion

Artificial neural network was adopted in this study, to investigate the optimization of mechanical properties of concrete made with bambara nut shell ash and quarry dust. Based on the findings of this investigation, partially replacing OPC with BNSA will result to reduced weight of concrete members due to the lower specific gravity of BNSA when compared with that of cement. The workability increased with increase in replacement of cement with BNSA and replacement of sand with quarry dust, because of increase in surface area and filler effect of BNSA inclusion in the concrete matrix. The initial and final setting times increased from 0 to 50% replacement intervals, due to the addition of BNSA in the concrete matrix. As the curing age increased, the flexural and compressive strength increased, while the compressive strength decreased with increase in the BNSA-QD contents beyond 22.5% replacement. This study recommends the use of bambara nut shell ash and quarry dust in concrete production as they will promote the protection of the ecological environment and reduce the gross project cost.

The optimum blend was obtained at a mix ratio of 0.775: 0.225: 1.55: 0.45: 4 at 22.5% replacement. The R-values obtained from the regression plot of the model were very close to 1, which validates the excellency of the ANN model. The computed T-value from the ANN predicted results were -2.74 and -3.45 for compressive and flexural strength respectively; which are less than the standard T-value of 2.09 obtained from the standard statistical table. This test of adequacy certifies that the modelled results are reliable and the network could be used to predict the compressive and flexural strength of BNSA-QD concrete at 95% confidence level. This study has shown that ANN modeling is superior to the conventional statistical approach.

References

Abdulla N.A. 2020. Using the Artificial Neural Network to Predict the Axial Strength and Strain of Concrete-Filled Plastic Tube. Journal of Soft Computing in Civil Engineering, 4(2): 63-84.

Alaneme G. U. and Mbadike E. M. 2021. Characterization of Bambara Nut Shell Ash (BNSA) in Concrete Production, Jurnal Kejuruteraan, 33(3): 633-646.

Alaneme G. U. and Mbadike E. M. 2021. Modelling of the mechanical properties of concrete with cement ratio partially replaced by aluminum waste and sawdust ash using artificial neural network. SN Applied Sciences, 1:1514.

Awodiji C. T. G., Onwuka D. O., Okere C. E., Ibearugbulem O. M. 2018. Anticipating the Compressive Strength of Hydrated Lime Cement Concrete Using Artificial Neural Network Model. Civil Engineering Journal, 4(12): 3005-3018,

Ayuba S., Uche O. U. A., Haruna S., Mohammed A. 2022. Durability Properties of Cement – Saw Dust Ash (SDA) Blended Self Compacting Concrete (SCC), Nigerian Journal of Technology (NIJOTECH), 41(2): 212 –221.

BS 12-1996. Specification for Portland cement, British Standards Institution, London.

BS 3140-1980. Methods of Test for Water for Making Concrete, Including Notes on the Suitability of the Water), British Standards Institution, London.

BS 882-1992. Specification for aggregates from natural sources for concrete, British Standards Institution, London.

Eze W. U., Yakubu M. K., Buba M. A, Kuzmin A., Santos-Ndukwe I. B., Ugbaja M. I. and Bayero A. H. 2022. Effect of Nano-Structured Bambara Nut Shell (Vigna Subterranea (L.) Verdc) As Filler on the Physical, Mechanical and Morphological Properties of Epoxy Matrix, Journal of Materials and Environmental Science, 13(10): 1155-1170.

Kosti´c S., and Vasovi´c D. 2015. Prediction model for compressive strength of basic concrete mixture using artificial neural networks. Neural Comput. Appl., 26: 1005–1024.

Nwa-David C. D. 2023a. Effect of Elevated Temperatures on Mechanical Properties of Concrete Blended with Nanosized Sawdust Ash and Rice Husk Ash. UNIZIK Journal of Engineering and Applied Sciences, 2(2): 404-415.

Nwa-David C. D. 2023b. The Behaviour of Concrete Made with Nanosized Periwinkle Shell Ash as Partial Replacement of Cement Under Varying Curing Conditions with Emphasis on its Compressive Strength, Journal of Materials Engineering, Structures and Computation, 2(3): 41-50.

Nwa-David C. D., and Ibearugbulem O. M. 2023. Model for Prediction and Optimization of Compressive Strengths of Cement Composites using Nanostructured Cassava Peel Ash as Partial Replacement of the Binder, Nigerian Research Journal of Engineering and Environmental Sciences, 8(1): 82-91.

Nwa-David C. D., Onwuka D. O., Njoku F. C., Ibearugbulem O. M. 2023a. Prediction of Fresh and Hardened Properties of Concrete Containing Nanostructured Cassava Peel Ash using Ibearugbulem's Approach, Engineering and Technology Journal, 41(5):1-14.

Nwa-David C.D., Onwuka D.O., Njoku F.C. 2023b. Prediction of Compressive Strength of Concrete containing Nanosized Cassava Peel Ash as partial Replacement of Cement using Artificial Neural Network, FUOYE Journal of Engineering and Technology, (FUOYEJET), 8(2): 253-259.

Nwobi-Okoye C.C., Umeonyiagu I.E., Nwankwo C.G.2013. Predicting the compressive strength of Concretes made with granite from eastern Nigeria using artificial neural networks, Nigerian Journal of Technology (NIJOTECH), 32(1): 13-21.

Ogbodo M. C. and Dumde D. K. 2017. Prediction of Concrete Strength Using Artificial Neural Network. International Journal of Advanced Research and Publications, 1(6): 74-77.

Olafusi O. S., Sadiku E. R., Snyman J., Ndambuki J. M., Kupolati W. K. 2019. Application of nanotechnology in concrete and supplementary cementitious materials: a review for sustainable construction, SN Applied Sciences, 1:580.

Oti J. E., Ukpata J., Osaretin U. J. 2019. Optimization of Bambara Nut Shell Ash Concrete Mix using Artificial Neural Networks and Genetic Algorithm. International Journal of Sustainable Built Environment 8(2): 303-315.

Oyebisi S., Igba T., Oniyide D. 2019. Performance evaluation of cashew nutshell ash as a binder in concrete production, Case Studies in Construction Materials, 11:1-18.

Rukzon S., Chindaprasirt P..2012. Utilization of bagasse ash in high strength concrete. Material Design. 34: 45–50.

Russell S.J., and Norvig P. 2013. Artificial Intelligence: a modern approach. Pearson Educational Inc., Upper Saddle River, New Jersey, USA.

Suescum-Morales D., Salas-Morera L., Jiménez J. R., García-Hernández L..2021. A Novel Artificial Neural Network to Predict Compressive Strength of Recycled Aggregate Concrete. Appl. Sci.,11: 11077.

Sutivisedsak N., Cheng H. N., Burks C.S., Johnson J. A., Siegel J. P., Civerolo E. L., and Biswas A. 2012. Use of Nutshells as Fillers in Polymer Composites, Journal of Polymer Environment, 20(2): 305 - 314.

Appendix 1

```
function [Y,Xf,Af] = myNeuralNetworkFunction(X,~,~)
%MYNEURALNETWORKFUNCTION neural network simulation function.
%
% Generated by Neural Network Toolbox function genFunction, 07-Feb-2022 21:04:37.
%
% [Y] = myNeuralNetworkFunction(X,~,~) takes these arguments:
%
%   X = 1xTS cell, 1 inputs over TS timsteps
%   Each X{1,ts} = 4xQ matrix, input #1 at timestep ts.
%
% and returns:
%   Y = 1xTS cell of 1 outputs over TS timesteps.
%   Each Y{1,ts} = 2xQ matrix, output #1 at timestep ts.
%
% where Q is number of samples (or series) and TS is the number of timesteps.

%#ok<*RPMT0>

% ===== NEURAL NETWORK CONSTANTS =====

% Input 1
```

```
x1_step1_xoffset = [0.5;0;0.5;0];
x1_step1_gain = [4;4;4;4];
x1_step1_ymin = -1;

% Layer 1
b1 = [2.4721795065877608;1.7225826153827672;-
1.5774221440891794;0.5297731930532783;0.18699427221487475;-
0.50553083659501885;0.96540788595234517;-1.8261676827603135;1.405049026701342;-2.5444881460782822];
IW1_1 = [-1.8553038388308851 1.6739773169671976 0.70310381380301668 -0.33675308266081033;-
2.0070422637091254 -1.2331684662348621 1.495686435176959 -0.87490372843804809;0.59448557460452944
2.2812588308342185 1.0254729456427978 0.98684505160923164;-0.023388174372029297 -
1.9107086265557094 0.65466936811779763 1.6699666311607195;-1.1870943268184524 -1.0549377705005292
1.8189963602377679 -0.63589248405045873;-0.14714374574601638 -2.4190514011245079 -
1.8641116621768088 1.28080107481976;0.85849034664694324 0.89218427394083977 2.2092666408889734 -
1.0131510743469541;-1.164775659244413 0.61089776227846826 -1.1708832461824858
1.5175116898664927;0.58187038038997929 0.68300363560971822 -1.7702939710726862 1.5586668142750879;-
1.9558353093148331 -0.23009043927539291 0.42518552026974665 -1.3238701432243845];

% Layer 2
b2 = [-0.92291106723101934;-0.92229757551448532];
LW2_1 = [-0.28286442495076991 0.47871439670501514 -1.1098775660594056 -0.071118774041882105
0.2101764522917029 0.78019042827729579 0.86845733735490538 0.54112226797488727 0.3132353632176787
-0.4419249754720751;-0.2226890964109714 1.2230937858207471 -0.049462368050943173 1.4668941146317931
-0.27304521861159198 0.7027642203692529 1.1450811850837024 1.032494898518636 0.11341195371050225 -
0.14279533307796349];

% Output 1
y1_step1_ymin = -1;
y1_step1_gain = [0.275482093663912;0.453514739229025];
y1_step1_xoffset = [18.38;5.17];

% ===== SIMULATION ========

% Format Input Arguments
isCellX = iscell(X);
if ~isCellX, X = {X}; end;

% Dimensions
TS = size(X,2); % timesteps
if ~isempty(X)
   Q = size(X{1},2); % samples/series
else
   Q = 0;
end

% Allocate Outputs
Y = cell(1,TS);

% Time loop
for ts=1:TS

   % Input 1
   Xp1 = mapminmax_apply(X{1,ts},x1_step1_gain,x1_step1_xoffset,x1_step1_ymin);

   % Layer 1
   a1 = tansig_apply(repmat(b1,1,Q) + IW1_1*Xp1);
```

```
    % Layer 2
    a2 = repmat(b2,1,Q) + LW2_1*a1;

    % Output 1
    Y{1,ts} = mapminmax_reverse(a2,y1_step1_gain,y1_step1_xoffset,y1_step1_ymin);
end

% Final Delay States
Xf = cell(1,0);
Af = cell(2,0);

% Format Output Arguments
if ~isCellX, Y = cell2mat(Y); end
end

% ===== MODULE FUNCTIONS ========

% Map Minimum and Maximum Input Processing Function
function y = mapminmax_apply(x,settings_gain,settings_xoffset,settings_ymin)
y = bsxfun(@minus,x,settings_xoffset);
y = bsxfun(@times,y,settings_gain);
y = bsxfun(@plus,y,settings_ymin);
end

% Sigmoid Symmetric Transfer Function
function a = tansig_apply(n)
a = 2 ./ (1 + exp(-2*n)) - 1;
end

% Map Minimum and Maximum Output Reverse-Processing Function
function x = mapminmax_reverse(y,settings_gain,settings_xoffset,settings_ymin)
x = bsxfun(@minus,y,settings_ymin);
x = bsxfun(@rdivide,x,settings_gain);
x = bsxfun(@plus,x,settings_xoffset);
end
```