Prediction of Compressive Strength of Concrete containing Nanosized Cassava Peel Ash as partial Replacement of Cement using Artificial Neural Network

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ORIGINAL RESEARCH

Abstract- The leaping impact of increased population and commercialization on global energy demand, has prompted more concern for sustainable development and strength evaluation of concrete structures. This study was carried out to improve the strength of concrete by adopting nanosized cassava peel ash (NCPA) as partial replacement of cement and to model its strength with artificial neural network (ANN). Data used for the model were obtained experimentally. At any percentage not exceeding 20 % NCPA replacement, the concrete is a suitable structural material. The neural network was adequately trained to capture the relationship between the compressive strength values of NCPA-concrete and their corresponding mix ratios at 7 days, 14 days, 28 days, 56 days, 90 days and 150days curing. A 6-10-1 network architecture was created. A total of four hundred (400) training data set were presented to the network. Two hundred and forty (240) of these were used for training the network, 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 had an R - value of 0.99909 which is very close to 1. This shows that the data used for training the network, have a good fit. The results obtained from the network are approximately the same as that obtained experimentally. The adequacy of the network was further tested using the Student's T test. The calculated T-value (-0.11) for the compressive strength of NCPA-concrete was less than that from the T-table (2.04) at 95% confidence level, proving that the network predictions are reliable. This model is reliable, time-effective and accurate for strength prediction of nanosized concrete.

Keywords- Nanosized Cassava Peel Ash, Mix ratio, Compressive strength, Artificial Neural Network, Concrete, Optimization.

1 INTRODUCTION

The application of concrete in the construction industry is growing rapidly and has led to stretched demand and consumption of concrete ingredients. Over the years, scholars have considered conventional concrete to be unattractive due to some limitations such as cracks and creep development, susceptibility to efflorescence, expansion and shrinkage (Awoyera, 2020; Bourchy et al. 2019). Although admixtures have been used to modify the concrete properties, the shortcomings are still discernible. The need for structural sustainability in the building industry have drawn the attention of researchers on improvement of structural concrete; this has led to nanosized concrete. Nanosized concrete is produced by adding nanosized materials or particles into concrete using the required 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). The need for concrete in increased infrastructural growth of most countries of the world has placed more demand on cement production. The environmental effect of cement production is a call for concern.

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According to (Baikerikar, 2014), over 0.9 tons of carbon dioxide (CO_2) is released in the environs during the production of 1 ton of cement and limestone deposits are expended in the process. The emission of CO_2 has led to the depletion of the ozonosphere with consistent effects such as earthquakes, flooding, hurricanes and arrival of new viruses. The cement industry is monopolized by a handful investors who can afford the expensive production cost of cement (Awodiji et al. 2018). The high cost of the product makes it difficult for average or low-income earners to construct their own houses. As a result of these, there is pressure to develop alternative binding materials.

The worth of concrete largely lies on its strength property (Obi and Adinna, 2023). Conventionally, laboratory trial mixes are employed to evaluate the compressive-strength of concrete and this is costly, energy and time consuming. One of the major reasons why most buildings collapse in Nigeria is weak concrete mixes (Olajumoke et al., 2009) and this has catastrophic environmental socio-economic aftermath (Arum, 2008). Researchers have tried to formulate and employ techniques that can be used for prediction of optimal strength in order to circumvent the challenges of experimental determination. In order to balance strength and cost, the most suitable proportioning of concrete constituents can be obtained using mathematical and computational models (Nuruddin et al., 2011). ANN have attracted more research interest because of its effectiveness and simplicity in computational model development (Nyarko et al., 2019). Low-concrete-strength is a major reason for most structural failure (Ojeda et al., 2021) and this strength can be predicted using artificial neural network.

ANN is a data processing system with some performance features common to biological neural networks (Fausett, 1994; Awodiji et al. 2018). ANNs, like humans, learn through examples. By a learning process, ANN is configured for a particular application, such as model recognition or data classification (Sebastia et al. 2003). The ANN model is predicated on numerous input and single output whereas regression models involve single input and single output and determines the scatter of measured input from the output. The ANN is the antidote for multi-dimensional problem. The modelled strength based on the ANN is more exact than the regression-based model (Thandavamoorthy, 2015).

ANN is adopted in this work to predict the compressive strength of concrete made with NCPA as partial replacement of the binder. The objective of this study is to experimentally assess the impact of 1.5 % interval of varying ratios of NCPA in the concrete mix so as to ascertain the optimum NCPA-cement composite with respect to compressive strength property of concrete, evaluating the applicability of ANN model soft computing approach in prediction of the properties of the concrete formed and validating the performance of the developed model using student's T-test. Also, the concept of nanosization employed in this research advances the existing knowledge on adoption of supplementary cementitious materials, concrete mixture optimization and good decision making on the batching of concrete that could be needed for certain concrete structures.

Abdulwahab and Uche (2021) studied the durability properties of self-compacting concrete made with cassava peel ash and recommended an optimum of 5% cement replacement for grade 35 compressive strength of CPA-SCC using 75 μm B.S. sieve to produce the ash. Nanosization was not considered and no form of modelling was employed by the authors.

Olonade et al. (2014), investigated the ascendancy of sulphuric acid on compressive strength of concrete made with blended cement-cassava peel ash. The authors observed that the concrete produced had relatively low-strength, when cured in sulphuric acid and due to the leaching effect of the acid, sulphuric acid solution led to the reduction in the mass of cement-CPA concrete. Their study did not consider NCPA and did not apply any modelling technique.

Although NCPA was employed in the study carried out by Nwa-David et al. (2023), ANN was not adopted. The authors applied Ibearugbulem's approach to model only the 28th day strength of NCPA-concrete. The compressive strength of the hydrated-lime cement-concrete was predicted with ANN by Awodiji et al. (2018) using some selected mix ratios. NCPA was not adopted in their study. Studies carried out Khan et al. (2013) also demonstrated the relevance and reliability of ANN technique in concrete model prediction. Contrasted with previous works, the distinguishing feature of this present study is the nanosization of cassava peel ash, percentage interval of partial replacement, curing age and the optimization model employed. Unlike the previous works that used Polynomial regression analysis, the present work applies a soft computing technique for optimization modelling. This paper determined experimentally the compressive strength of nanosized cassava peel ash-cement concrete, formulated ANN model that can be used to predict the strength behaviour and statistically evaluated the model using percentage error and student's T-test tools.

2 Materials And Methods

2.1 Materials

The materials used for this study included, Ordinary Portland Cement, Nanosized Cassava Peel Ash (NCPA), water, sharp-river sand, and crushed granites whose maximum size was 20 mm diameter. The granite was obtained from the quarry site at Ishiagu, Ebonyi State, Nigeria. The sand was sourced from Imo River, Imo State of Nigeria. It was sieved through 10 mm British Standard test sieve to remove cobbles. *BUA* brand of Ordinary Portland Cement that conformed to the requirements of BS 12 (1996) was used. Cassava peels were obtained from cassava peels dump site at a garri processing centre in Ohaji/Egbema local government area of Imo State. The cassava peels were gathered and dried under the sun. The cassava peel was burnt in a kiln at a temperature of about 700 °C in 60 minutes in a control incineration set-up. The produced ash was sieved with 200nm nano-sieve to obtain nanosized cassava peel ash (NCPA) as shown in plate 2. Water that is fit for drinking was obtained from a borehole at the laboratory and it conformed to the requirements of BS 3140 (1980).

Plate 1: Cassava Peels

Plate 2: Nanostructured Cassava Peel Ash

2.2 Methods

Three methods were employed in this research and they were; experimental, prediction and statistical methods. Experimentally, a total of nine hundred and eighteen (918) concrete-cubes of 150 mm x 150 mm x 150 mm were produced with OPC and NCPA using varied percentage replacement with NCPA at 1.5% intervals. A replicate of three cubes were cast for each percentage replacement. A mix proportion of 1:1.5:3 (blended cement: sand: granite) was used for the concrete. Batching was done by weight and at varying water-binder ratio. Mixing was done manually on a smooth concrete pavement. The ash was first thoroughly homogenized with cement at the desired proportion and the homogeneous blend was then mixed with the fine-coarse aggregate mix, also at the required proportion. Water was then added gradually and the entire concrete heap was mixed thoroughly to ensure uniformity. The mixture was then introduced into 150 mm ×150 mm × 150 mm metal moulds; in three layers and compacted with the tamping rod 25 stroke per layer and the top finish with the trowel and label 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 experimental values of the compressive strengths of NCPA-concrete were utilized to formulate ANN prediction model. This was implemented using the neural network toolbox found in the MATLAB R2015a software. The mix proportions of water-cement ratio, Portland cement, NCPA, river sand, granite chippings and curing age represented the input vectors used for the training of the networks, while their corresponding compressive strength values represented their output vector. Four hundred (400) training data set were presented to the network. Two hundred and forty (240) of these were used for training the network, sixty (60) were used for validation, and another sixty (60) were used for testing the network's performance. This division was achieved by the use of the 'dividerand' function and the network objects. The training function used was the "trainlm" (i.e. the Levernberg-Marquardt back propagation training function), while the activation function used was the "Tansig" i.e. the tangent sigmoid function. The developed arrangement of neurons within the neural network (ANN Architecture) is 6-10-1. It has 6 input neurons, 10 hidden layer neurons and one output neuron. An error measure known as the mean square error is used for back propagation algorithm. The mean square error is expressed as;

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

Where,

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

o_k= Actual output obtained from o_k output unit

The Levernberg-Marquardt (LM) algorithm is used for this study. Each weight is thought to be in an N – dimensional error space and they act as independent variables. The shape of the corresponding error surface is obtained by the error function in combination with the training set. Applying the LM algorithm, Equation (1) can be re-written as:

$$E_p(\beta) = \sum_{k=1}^{p} [t_k - f(O_{k,\beta})]^2 \quad (2)$$

Where,

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

f(ok, β)= Actual output obtained from O_k output unit.

Ep(β) = Mean square error;

B = Parameter vector;

o_k= Measured vector;

f= Functional relationship.

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

The model performance was further evaluated with student t-test statistical methods. The adequacy of the network predictions against the experimental values were tested using the student's t-test as presented in equation (3)

$$T = \frac{DA\,X\sqrt{N}}{S} \quad (3)$$

Where,

$$\sum \frac{Di}{N} \quad (4)$$

$$S = \sqrt{S^2} \quad (5)$$

$$\sum \frac{(DA - Di)^2}{(N-1)} \quad (6)$$

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

3 Results and Discussion

3.1 Properties of NCPA and Aggregates

The chemical composition of the NCPA was determined and presented in Table 1 and it is observed that NCPA contains 61.70% SiO_2, 12.50% Al_2O_3 and 2.52% Fe_2O_3, whose percentage sum is in line with ASTM C 618 (2008) requirement. NCPA has lesser specific gravity of 2.10 when compared with the specific gravity of the cement (3.02). This implies that partially replacing OPC with NCPA will result to reduced weight of concrete members. NCPA is 1.4 times lighter than cement.

Table 1. Chemical Composition of BUA brand of OPC and Nanostructured Cassava Peel Ash (NCPA)

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

The sand has physical properties of 1654 kg/m^3, 2.65 and 2.92 corresponding to its values of uncompacted bulk density, specific gravity and fineness modulus respectively. The river sand has coefficient of uniformity and coefficient of curvature values of 2.70 and 0.96 respectively obtained from Figure 1.

The granite has physical properties of 1522 kg/m^3, 2.75 and 3.28 corresponding to its values of uncompacted bulk density, specific gravity and fineness modulus respectively. The coarse aggregate has coefficient of

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uniformity and coefficient of curvature values of 1.828 and 1.237 respectively obtained from Figure 1. Both aggregates satisfied the requirements of BS 882 (1992). The materials were confirmed to be suitable for the concrete production.

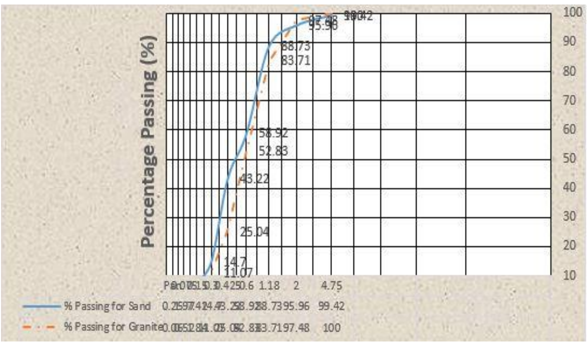

Fig 1: Grain size distribution curve of the aggregates

3.2 Concrete Compressive Strength

Figure 2 show the result of the compressive strength for 7, 14, 28, 56, 90 and 150 days respectively. The result showed that the compressive strength increased as the percentage replacement of the Portland cement with nanostructured cassava peel ash (NCPA) increased and as the curing age increased. From the figure, it can be seen that inclusion of NCPA in concrete mix is effective in increasing the compressive strength of concrete. This could be attributed to silica (SiO_2) and alumina (Al_2O_3) of NCPA content being larger than those of OPC as indicated in Table 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 et al. 2014). It can be observed that the compressive strength increased up to 19.5% replacement of cement with NCPA. The addition of this nanomaterial (NCPA) to the concrete helped to fill the pores existing in the matrix in order to provide an exceptional surface area to volume ratio, improved basic property and reactivity of the material. This in turn enhanced the strength of the concrete. The strength improvement is believed to continue as long as the curing period is prolonged to allow completion of hydration. The optimum compressive strength of 36.90 N/mm² was achieved at 19.5 % replacement at 150 days of age.

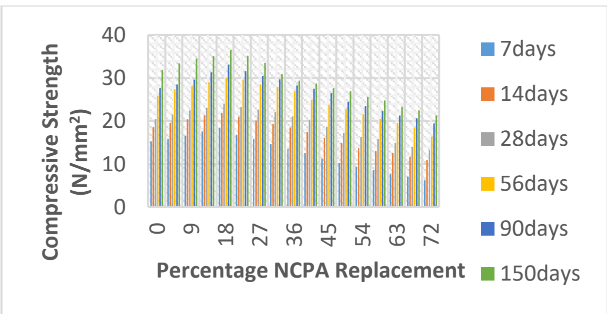

Fig. 2: Compressive Strength of NCPA-Cement Concrete with varying curing days.

3.3 ANN Model Development

Performance validations conducted on the formulated neural network model are presented in Plates 3 to 6. A gradient of 0.0488 targeting 1.0e-07 was achieved at this point after performing 6 validation checks before convergence as shown in Plate 3. It was also observed that the best validation check occurred at the 18th epoch at a mean square error of 10^{-2} and best performance at 0.0337. The gradient at the very last epoch (Mu) was 0.01. Plate 3 shows the training state for the ANN model; the errors are repeated sometime after epoch 18 and the test was stopped at epoch 24. Epoch 18 is selected as the base and its weights are chosen as the final weights.

Plate 4 shows the mean squared error and validation performance of the network starting at a large value and descending to a small value. The training, validation, and test are displayed in the plot. It was also observed that the optimal validation check occurred at the 18th epoch with best performance of 0.033726 and the process is ended at epoch 24 as shown in the x-axis of the plot. Plate 5 presents the error histogram chart with 20 bins for the validation, test and training, in ANN modelling. The error histogram of the plate depicts that the 14th bin has zero error at 0.003133 and produced the best performance for the network. As it is shown in the figure, the zero error is indicated with a yellow line in the middle with 25 instances in the training set.

Plate 6 shows the coincidence between the target and response variables which is the coefficient of determination for validation, training and test steps, respectively. The R value is an indication of the relationship between the outputs and targets. If R = 1, then there is a linear relationship between the output and the targets (Awodiji et al., 2018). The statistical computation results obtained show satisfactory performance in terms of prediction-accuracy of the ANN model with 0.9992, 0.9980, and 0.9993 values obtained for training, testing, validation respectively and finally 0.9991 for the combination of the three. These values are very close to 1, showing that the artificial neural network model formulated for predicting compressive strength of NCPA-concrete has good predicting ability.

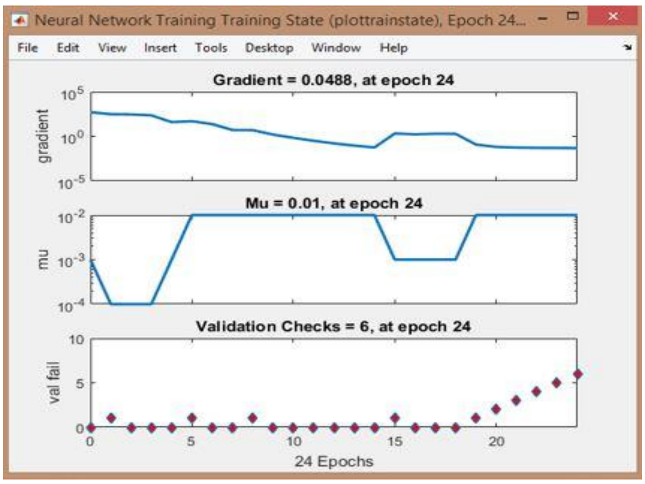

Plate 3: ANN training state

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From the regression plot, the R-values confirms acceptable accuracies of the model in both the training and validation steps. Table 2 shows the comparison of experimental results against neural network prediction for the compressive strength of NCPA-Cement composites using percentage error method. The modelling and simulation of the neural network with the data obtained experimentally has produced considerable encouraging results. Overview, it can be seen from Table 2 that the highest percentage error obtained was 7.15% 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. Predictions from the formulated model were further examined for adequacy against their experimental values using the student's t-test. Table 3 presents the result obtained from this test.

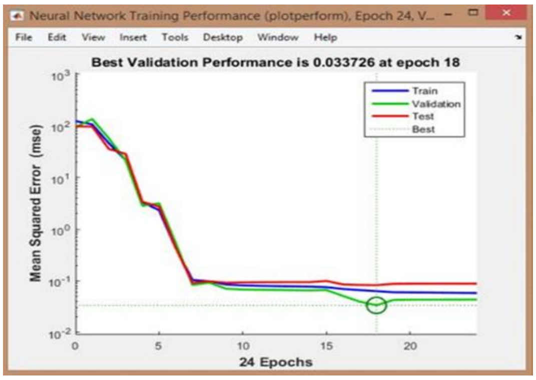

Plate 4: Validation performance of the ANN

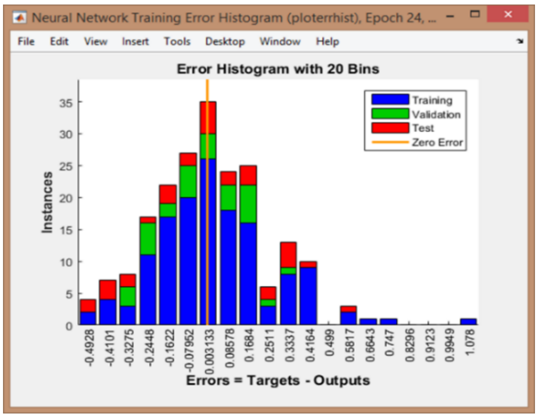

Plate 5: ANN error histogram

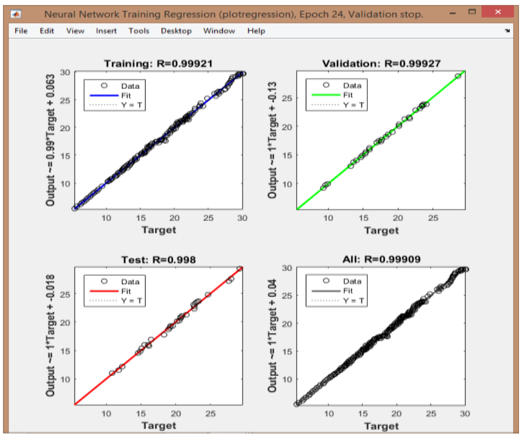

Plate 6: Regression plot for training, test and validation of the ANN

Table 2. Comparison of experimental results against neural network prediction for the compressive strength of NCPA concrete using percentage error method.

Mix Label	E_x (N/mm²)	N_p (N/mm²)	Error	% Error
B_1	15.30	15.339	-0.039	-0.25425
B_2	15.60	16.210	-0.61	-3.76311
B_3	16.10	16.320	-0.22	-1.34804
B_4	16.60	17.021	-0.421	-2.47342
B_5	17.40	17.424	-0.024	-0.13774
C_1	18.60	18.642	-0.042	-0.2253
C_2	19.20	19.457	-0.257	-1.32086
C_3	19.90	19.834	0.066	0.332762
C_4	20.40	20.423	-0.023	-0.11262
C_5	20.90	20.776	0.124	0.596843
D_1	20.50	21.235	-0.735	-3.46127
D_2	21.20	21.845	-0.645	-2.95262
D_3	21.80	21.569	0.231	1.070982
D_4	22.50	22.522	-0.022	-0.09768
D_5	23.00	23.234	-0.234	-1.00714
E_1	25.90	24.171	1.729	7.1532
E_2	26.50	26.435	0.065	0.245886
E_3	27.60	27.578	0.022	0.079774
E_4	28.10	27.835	0.265	0.952039
E_5	28.60	28.722	-0.122	-0.42476
F_1	27.70	27.345	0.355	1.298226
F_2	28.30	28.240	0.06	0.212465
F_3	28.90	28.458	0.442	1.553166
F_4	29.60	29.456	0.144	0.488865
F_5	31.00	31.456	-0.456	-1.44964
G_1	31.80	32.324	-0.524	-1.62109
G_2	32.80	32.671	0.129	0.394846
G_3	33.70	33.586	0.114	0.339427
G_4	34.50	34.236	0.264	0.771118
G_5	35.00	34.898	0.102	0.29228

The computed T-value from the ANN predicted results is -0.11 which is less than the standard T-value of 2.04. 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 7, 14, 28, 56, 90 and 150 days' compressive strength of NCPA-concrete at 95 % confidence level. This means that neural networks have been satisfactorily trained, as all the outputs given by the network are close to the values of the experimental results.

4 Conclusion

From the result of this work, the following conclusions were made; nanosized cassava peel ash increases the strength of the concrete as the curing period increases. At a percentage not more than 20% NCPA replacement, the concrete strength can be improved. It proved that the agricultural waste; cassava peel ash, can be processed and used as cementitious material for construction of light-weight structures. The modelled values were close to that of the experimental record. The adequacy of the network was further tested using the Student's T-test. The T-value calculated for the compressive strength of NCPA-concrete was lower than that from the T-table at 95%

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confidence level, proving that the network predictions are reliable.

Table 3. Statistical student's T-test for ANN model validation

S/N	$D_i = E_x - N_p$	$D_A = (\sum D_i)/N$	$D_A - D_i$	$(D_A - D_i)^2$
1	-0.039	-0.008733	0.030267	0.000916
2	-0.61	-0.008733	0.601267	0.361522
3	-0.22	-0.008733	0.211267	0.044634
4	-0.421	-0.008733	0.412267	0.169964
5	-0.024	-0.008733	0.015267	0.000233
6	-0.042	-0.008733	0.033267	0.001107
7	-0.257	-0.008733	0.248267	0.061637
8	0.066	-0.008733	-0.07473	0.005585
9	-0.023	-0.008733	0.014267	0.000204
10	0.124	-0.008733	-0.13273	0.017618
11	-0.735	-0.008733	0.726267	0.527464
12	-0.645	-0.008733	0.636267	0.404836
13	0.231	-0.008733	-0.23973	0.057472
14	-0.022	-0.008733	0.013267	0.000176
15	-0.234	-0.008733	0.225267	0.050745
16	1.729	-0.008733	-1.73773	3.019716
17	0.065	-0.008733	-0.07373	0.005437
18	0.022	-0.008733	-0.03073	0.000945
19	0.265	-0.008733	-0.27373	0.07493
20	-0.122	-0.008733	0.113267	0.012829
21	0.355	-0.008733	-0.36373	0.132302
22	0.06	-0.008733	-0.06873	0.004724
23	0.442	-0.008733	-0.45073	0.20316
24	0.144	-0.008733	-0.15273	0.023327
25	-0.456	-0.008733	0.447267	0.200048
26	-0.524	-0.008733	0.515267	0.2655
27	0.129	-0.008733	-0.13773	0.01897
28	0.114	-0.008733	-0.12273	0.015063
29	0.264	-0.008733	-0.27273	0.074383
30	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, $T = T_{(0.05, n-1)} = T_{(0.05,29)} = 2.04$

5 Recommendation

Based on the outcome of this study, the following recommendations are made; artificial neural network is suitable and reliable for prediction of compressive strength concrete containing nanosized cassava peel ash. And so, the model should be used to determine compressive strength NCPA-concrete given any mix ratio and vice versa. Further investigations should be carried out on the application of ANN to predict other important properties of concrete, such as modulus of rupture, elastic modulus, flexural strength and shear modulus.

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