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Modelling Slump of Concrete Containing Natural Coarse Aggregate from Bida Environs Using Artificial Neural Network

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ABSTRACT

Consumption of crushed granite as coarse aggregate in concrete has led to devastating environmental and ecological consequences. In order to preserve local and urban ecology therefore, substitute aggregate such as naturally occurring stone with the propensity of reducing this problem was studied. Furthermore, artificial Neural Network (ANN) models have become the preferred modeling approach due to their accuracy. Thus, in this paper, MATLAB software was used to develop ANN models for predicting slump of concrete made using Bida Natural Gravel (BNG). Four model architectures (5:5:1; 5:10:1; 5:15:1 and 5:20:1) were tried using a back-propagation algorithm with a tansig activation function. The performance of the developed models was examined using Mean Square Error (MSE), Correlation Coefficient (R) and Nash-Sutcliffe Efficiency (NSE). Results showed that 5:20:1 model architecture with MSE of 8.33e-27, R value of 98% and NSE of 0.96 was the best model. The chosen 5:20:1 ANN model also out performed Multiple Linear Regression (MLR) model which recorded MSE of 0.83, R value of 88.68% and NSE of 0.87. The study concluded that the higher the neuron in hidden layer of ANN slump model for concrete containing BNG, the better the model.

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1. Introduction

Workability of concrete is a measure of the ease with which fresh concrete can be mixed, placed, consolidated, and finished without loss or minimal loss of homogeneity [1-3]. Fresh properties of concrete are as though important as the strength properties since the strength of concrete has a direct bearing with the handling of the material (transportation, placement, compaction and surface finishing). Slump test is often used to measure the workability of concrete in the laboratory and in the field. Concrete slump is measured using a slump cone and slump value is recorded from the topmost part of the slumped concrete after compaction. Depending on the shape and nature of the slumped concrete, three categories of slump can be observed. These are true slump, shear slump and collapsed slump as shown in Figure 1 [3]. Properties such as water-cement ratio and aggregates type, grading, texture and shape have been reported to affect the workability of concrete [4-7]. Specification of construction works usually require testing the fresh concrete to ascertain that the required workability is met. To prepare concrete with the workability of interest, designers usually result to trying several mix combinations. This process is inarguably expensive, time consuming and leads to wastage of materials. Statistical and Artificial Intelligence (AI) models have been used for forecasting structural engineering problems as well as the slump and strength of different types of concrete and mortar with the intention to save cost and time [8-31]. Furthermore, Artificial Neural Network (ANN) models for predicting the slump of different ready-mix concrete types have been developed. [32] developed ANN model for predicting strength of normal and high strength ready mixed concrete using back propagation algorithm. Similarly, [33] used ANN for forecasting the workability of concrete containing supplementary cementitious materials. [34] applied ANN for predicting slump of ready mixed high strength concrete while [35] also utilised ANN methodology for modeling ready mix concrete slump using randomised disjoint sets. [36] used seven concrete mix ingredients in modeling the slump and strength of concrete. All these researches yielded satisfactory prediction capability and established that ANN is a powerful and superior modelling tool than statistical approach. However, majority of these research efforts used crushed granite to produce concrete specimens.

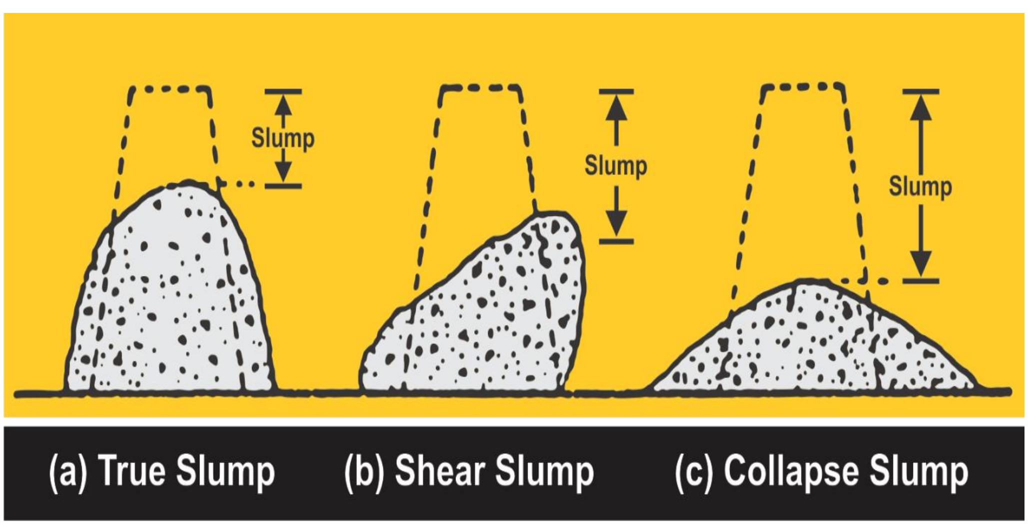

Fig. 1. Types of Concrete Slump [3].

The consumption of concrete in the Nigerian construction industry has continued to increase due to the extemporaneous increase in population and by consequence, the need to provide adequate infrastructure. Crushed granite is the common and conventional coarse aggregate recommended for use in concrete. Proximity of construction work to quarry locations has been a major concern for construction practitioners in Nigeria. As such, Bida Natural Gravel (BNG) was used to substitute crushed granite in this research. BNG occur as a natural stone in the Bida Basin, North Central Nigeria. It has been used from ancient times in the production of concrete. Some notable research efforts where BNG was used as coarse aggregate are available in literature. [37] and [38] studied the slump and strength of self-compacting concrete using BNG. No modelling approach was considered in the research. In the same vein, [39], [40] and [41] reported satisfactory performance of BNG in normal strength concrete. It is of note that among these research efforts, only [40] attempted to model the slump of normal strength concrete containing BNG using statistical technique. Statistical technique requires considering linear, pure quadratic, interaction, full quadratic and reduced full quadratic models to obtained the best fit model. This process of trying to achieve the best model is time consuming. Information on the use of ANN to model the slump of concrete made using BNG is therefore, hard to come by. It is against the foregoing that this research attempts to develop ANN model for predicting slump of concrete containing BNG since ANN is adjudged to possess better prediction accuracy than statistical technique [42-44].

The objective of the study is to prepare concrete mixes using different combination of concrete constituent and develop ANN models based on different model architectures for predicting the slump of concrete made using BNG. This study is novel in the sense that the concrete slump data (using BNG) have not been used by any researcher.

2. ANN overview

Artificial Neural Network (ANN) have been reported to possess better prediction capabilities than statistical techniques [42-44]. ANN is a computerized structure with the propensity to process data in similar fashion like biological neural system in the human brain. They are mostly used in prediction, classification and pattern recognition problems to model relationships between parameters [45 – 46]. In the general sense, ANN learn the features available in given data or examples and establish relationships between stored data and new data adaptively using highly sophisticated means. Since neural networks learn with known data of a given problem to obtain knowledge, it can be used to treat unfamiliar data after a successful training process. Training an ANN requires the supply of input and output (target) data pairs and setting small random weights (coefficients) to initialize the network. The combination of input is applied and the output is estimated according to the customized initial weights. The output obtained is entirely different from the target and the error in each neuron is estimated. The error is mathematically used to adjust the weights so that the output is similar to the target. This is process is used to train feed-forward networks and is termed back propagation algorithm. The feed forward, back propagation algorithm procedure adopted in this research is shown in Figure 2 [47]. There are however several training algorithms based on back propagation. Common among these methods include; Gradient descent, Newton Method, Conjugate gradient, Quasi-Newton and Levenberg-Marquardt algorithm. The choice of selecting which algorithm to use depends on the available computer memory and the prediction speed required. The gradient descent has been reported to be the slowest. Although it requires less memory to operate. The adopted algorithm is the Levenberg-Marquardt algorithm which is adjudged to be the fastest. Performance evaluation of the common algorithms is given in Figure 3.

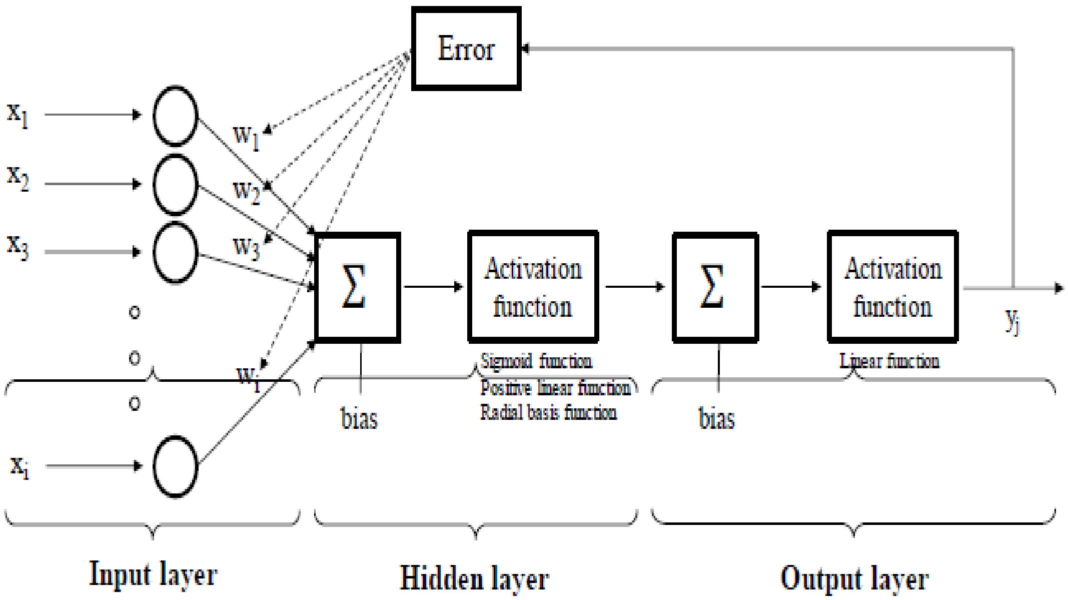

Fig. 2. Structure of Artificial Neural Network [47].

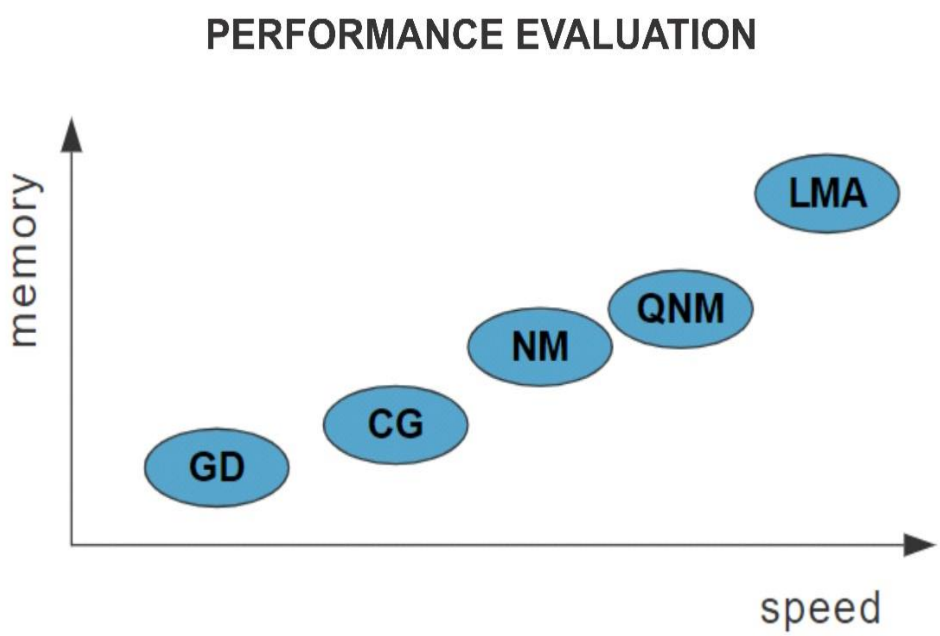

Fig. 3. Performance evaluation of Backpropagation Algorithms.

3. Experimental programme

3.1. Materials and their properties

Ordinary Portland Cement (OPC) categorized as grade 42.5 according to [48] with a Specific Gravity (SG) of 3.16 obtained from local retailer was used as binder.

River sand collected from Chanchaga river possessing SG of 2.52, Fineness Modulus (FM) of 2.74 and water absorption of 3.5% was used as fine aggregate.

BNG shown in Figure 4 was used as coarse aggregate in the study. The stone was sieved, washed, dried and those with maximum size of 14mm was used. The stone recorded a SG of 2.64 and a water absorption of 1.57%. All preliminary tests on aggregates were conducted based on [49] guidelines. The aggregates also fulfilled the grading limits of [50].

Fig. 4. Representative Sample of Bida Natural Gravel.

Potable water devoid of deleterious substance and free from algae obtained from tap in Civil Engineering Laboratory, Federal University of Technology, Minna, Nigeria was used for mixing and curing.

3.2. Procedure

Mix design was conducted by absolute volume method. Water, cement and aggregates were weighed according to batch quantities given in Table 1 and a mini concrete mixer was used to mix the materials as shown in Figure 5. Water was first put in the mixer. Fine aggregate and cement were added to the water and mixing was done for 120 seconds. BNG in the required amount was added to the mixture and mixing continued for another 120 seconds. For each of the mix combinations provided in Table 1, concrete was prepared and the slump loss was examined in accordance to [51] as shown in Figure 5.

Fig. 5. Mixing of concrete constituents.

Fig. 6. Measurement of concrete slump.

3.3. Collection of data

Slump of concrete is governed predominantly by water-cement ratio (w/c), total aggregate to cement ratio and coarse aggregate (BNG) to total aggregate ratio. Design of experiment in Minitab software (version 2017) [52] was used to generate 36 mix combinations based on these three parameters. Absolute volume method was thereafter used to calculate the water, cement, river sand and BNG contents in kg/m^3. Water-cement ratio (w/c), water, cement, river sand and BNG content were supplied to the ANN as input data while the average slump test results obtained from three (3) trials for the 36 experimental points were fed to the ANN as output data. The mix details and measured slump given in Table 1 while the descriptive statistics of the input and output data pairs are given in Table 2.

Table 1
Mix detail for 1m^3 of concrete and slump of fresh concrete.

S/N	W/C	Water (kg/m^3)	Cement (kg/m^3)	Sand (kg/m^3)	BNG (kg/m^3)	Slump (mm)
1	0.6	221.71	369.36	664.90	997.35	65
2	0.5	156.33	312.67	843.91	1031.60	10
3	0.4	208.93	522.32	705.19	861.76	40
4	0.6	181.66	303.02	817.85	999.76	25
5	0.5	248.25	496.74	521.59	968.64	192
6	0.5	248.01	496.02	669.48	818.34	195
7	0.4	159.95	399.76	629.67	1169.60	7
8	0.6	221.71	369.60	582.39	1081.30	178
9	0.6	283.72	472.86	496.50	921.83	225
10	0.6	221.47	369.12	747.41	913.39	178
11	0.4	159.71	399.03	808.20	987.70	0
12	0.5	248.25	496.26	595.66	893.37	190
13	0.5	191.80	383.84	690.95	1036.43	52
14	0.6	283.23	472.14	637.15	778.77	270
15	0.5	156.57	313.15	657.90	1221.71	10
16	0.4	209.41	523.28	549.34	1020.27	26
17	0.4	209.17	522.80	627.26	941.13	22
18	0.5	191.80	383.59	776.60	949.10	8
19	0.4	129.07	322.80	871.89	1065.62	0
20	0.6	182.15	303.50	637.39	1183.84	3
21	0.4	129.31	323.52	679.61	1262.00	0
22	0.5	156.57	312.91	751.03	1126.42	2
23	0.6	181.91	303.26	727.86	1091.68	4
24	0.4	159.71	399.52	718.94	1078.65	3
25	0.4	129.31	323.28	775.87	1163.57	0
26	0.6	283.47	472.38	566.95	850.42	230
27	0.5	192.04	384.08	605.07	1123.76	60
28	0.55	242.94	441.50	695.54	850.18	215
29	0.55	179.73	326.90	988.90	809.17	2
30	0.55	179.73	327.62	810.62	990.83	4.5
31	0.45	201.69	462.48	728.35	890.23	32
32	0.45	152.23	338.24	1023.16	837.15	0
33	0.45	152.47	338.96	838.84	1025.09	2
34	0.40	148.37	370.81	648.73	1204.83	6
35	0.60	206.76	344.75	603.14	1120.14	154
36	0.50	178.53	357.30	625.09	1160.92	33

Table 2
Descriptive Statistics of Input and Output Data.

Parameter	Water-cement ratio	Water content kg/m^3	Cement content kg/m^3	Sand content kg/m^3	BNG content kg/m^3	Slump (mm)
Mean	0.50	194.10	390.54	703.30	1011.85	68
Std error of mean	0.01	7.20	12.19	19.94	21.78	15
Median	0.50	186.97	370.21	685.28	1010.01	24
Std. deviation	0.60	221.71	73.14	119.63	130.67	88
Variance	0.08	43.22	-	-	-	-
Range	0.20	154.64	220.27	526.66	483.23	270
Minimum	0.40	129.07	303.02	496.50	778.77	0
Maximum	0.60	283.72	523.28	1023.16	1262.00	270

3.4. Data pre-processing

ANN input and output data sets are often not on the same numerical scale. Activation functions used to transform weighted sum of inputs to give outputs are usually nonlinear functions of sigmoid nature. These functions are typically sensitive to data within specific range. Furthermore, experimental data usually contain noisy and omitted observations and in most cases of inconsistent nature. Procedures encompassing data reduction, data transformation, data integration, data cleaning and data normalization have been reported to improve the effectiveness and precision of ANN models [53-58]. In order to fairly judge the neural network identities, data normalization was performed on the data sets. Consequently, improved min-max normalization technique shown in Equation 1 was used to transform the input data to a uniform scale between -1 and +1. This method has been reported to be effective for sigmoid activation function which was adopted in this study [59-60].

$$Nd = 2\left(\frac{x-xmin}{xmax-x\,min}\right) - 1 \qquad (1)$$

Where;
Nd is the normalized data
x is the input parameter
xmin is the minimum value of x and
xmax is the maximum value of x.

4. Methods

4.1. ANN modelling of concrete slump

4.1.1. ANN model implementation

Neural Network Toolbox available in MATLAB 2015 software (Version R2015a) [61] was used to implement a back propagation neural network algorithm for the study.

4.1.2. Preparing training, validation and test data sets

The architecture of ANN comprises essentially of input, hidden and output layers. The most basic ANN is the single layer neural network which comprises of only one layer of input nodes. A multi-layer network which is the widely used ANN today comprises of more than one layer of input nodes [62-63]. ANN is structured to function like the human brain. As such, it performs knowledge acquisition from interconnection of input data (x) and corresponding output data (y) based on an iteration process of weight (coefficient) and in most cases bias (constant) adjustments up until the error between the actual output and model output is negligible in line with preselected performance metrics as shown in Figure 1 [64-67]. This process is known as the back-propagation training algorithm and was adopted in this study. New sets of input data are supplied to the network based on fixed weights and bias of final training process to generate outputs depending on the learnt input/output pair.

4.1.3. ANN slump model

Approximately 70% (26 data points) of the preprocessed data was supplied to the ANN as training data while 15% (5 data points each) was supplied as testing and validation data in each case. The input data were supplied to the neurons in the input layer and are each treated with a weight coefficient in addition to a constant to obtain a weighted input sum given in Equation 2.

$$\beta = \sum_{i=1}^{n} xi.wij + b1 \tag{2}$$

Where;

β is the weighted sum of input and bias
xi is input data i
wij is the weight associated with the hidden layer and
b1 is the constant associated with hidden layer.
Equation 2 was treated with a tansig activation function given in equation 3 to obtain the first layer slump output given in equation 4.

$$\alpha = \frac{2}{1+e^{-2x}} - 1 \tag{3}$$

Where;

α is the activation function

x is the weighted sum of inputs β

$$\mathbf{\Gamma}_{\text{hidden}} = \alpha \sum_{i=1}^{n} xi.wij + b1 \tag{4}$$

Where;

$\mathbf{\Gamma}_{\text{hidden}}$ is the hidden layer slump output.

The first (hidden) layer slump output $\mathbf{\Gamma}_{\text{hidden}}$ was provided to the neuron in the output layer and are further processed with new weight sets and bias. The weighted sum was further treated with a linear activation function given in equation 5 to obtain the overall model output given in equation 6.

$$f(x) = x \tag{5}$$

$$\boldsymbol{\Gamma}_{\text{output}} = \phi\left(\sum_{i=1}^{n} wij\, \Gamma\left(\alpha \sum_{i=1}^{n} xi.wij + b1\right) + b2\right) \tag{6}$$

Where;

$\boldsymbol{\Gamma}_{\text{output}}$ is the output of the entire ANN

$\boldsymbol{\phi}$ is a linear activation function $f(x)$

wij is the weight associated with the output layer and

b2 is the bias associated with the output layer

4.1.4. Evaluation of the ANN slump model

The slump model was trained using back propagation algorithm. The sequence requires updating the connection weights and biases according to the learning capacity of the network. The iterative process was allowed to continue up until the network was able to recognize the smallest error between the actual experimental slump result and that obtained by the model based on the parameters given in table 2. The performance of the trained slump model was examined using Mean Square Error (MSE), Correlation Coefficient (R) and Nash-Sutcliffe Efficiency (NSE) given in equations 7, 8 and 9 respectively. The MSE is a measure of the error margin between the actual and the predicted output. It also depicts the deviation of the predicted output from the actual output. Thus, the smaller the MSE, the smaller the error margin and the better the model. R value range from 0 to 1 or from 0 to 100 percent with values closer to 100% signifying a high goodness of fit [43]. The Nash-Sutcliffe Efficiency (NSE), whose values ranges from –∞ to 1 is a measure of the goodness of fit of a predicted model as compared to the actual output. Thus, the closer the NSE value is to 1, the better the model. Although [10] suggests that NSE greater than 0.8 is considered good.

Table 2
Parameters used to train ANN models.

Parameter	Configuration
Input data	w/c, water, cement, sand and BNG content
Output data	slump
Maximum number of epochs	1000
Performance goal	0
Minimum gradient	$1x10^{-07}$
Validation Check	6
Training function	TrainLM
Activation function	Hidden layer – Tansig; Output layer - Purelin
ANN architectures tried	5:5:1; 5:10:1; 5:15:1 and 5:20:1

$$MSE = \frac{\sum_{i=1}^{n}\left(\Gamma output(i) - \Gamma actual(i)\right)^2}{n} \tag{7}$$

$$R = \left[\frac{\sum_{i=1}^{n}(\Gamma actual(i)-\overline{\Gamma actual(\iota)})(\Gamma output(i)-\overline{\Gamma output(\iota)})}{\sum_{i=1}^{n}(\Gamma actual(i)-\overline{\Gamma actual(\iota)})^{2}\sum_{i=1}^{n}(\Gamma output(i)-\overline{\Gamma output(\iota)})^{2}}\right]^{2} \quad (8)$$

$$NSE = \frac{\sum_{i=1}^{n}(\Gamma actual(i)-\Gamma output(i))^{2}}{\sum_{i=1}^{n}(\Gamma actual(i)-\overline{\Gamma actual(\iota)})^{2}} \quad (9)$$

Where;

$\mathbf{\Gamma}_{output}$ (i) is the slump output from the ANN model

$\mathbf{\Gamma}_{actual}$ (i) is the actual experimental slump result

$\overline{\Gamma actual(\iota)}$ is the average actual slump,

$\overline{\Gamma output(\iota)}$ is the average slump output from the ANN model and

n is the sample size.

5. Results and discussion

ANN models were developed with 5, 10, 15 and 20 hidden neurons. As depicted in Table 3, the performance of the models based on MSE, R and NSE are presented. MSE reduced with increase in the number of hidden neurons. Model with 20 hidden neurons gave the least MSE of $8.33e^{-27}$ and proved to be the model with best performance. This was closely followed by the model with 15 hidden neurons which recorded MSE of $1.42e^{-22}$. Models with 5 and 10 hidden neurons recorded MSE of 0.000519 and 0.000194 respectively. An inferior performance when compared to the models with 15 and 20 hidden neurons. The overall R values for the models were between 89 and 99 %. In order to verify the variability in the slump data which was accounted for by the slump model in the training, testing, validation and overall phases, the R metric was used to judge the model with the best performance. From Figure 3, 5:5:1 model architecture recorded 99%, 66%, 99% and 91% R value for the training, testing, validation and overall model respectively. It is evident that the 5:5:1 model architecture possessed a high R value in the training and validation phases. This was not the case in the testing and overall model when compared to the 5:10:1 model architecture which recorded 87% R in the testing phase. 5:15:1 model had R metrics of 99%, 98%, 97% and 99% in the training, testing, validation and overall model. The model with 5:20:1 recorded overall R of 98%, one percent short of the highest R recorded by the model with 5:15:1. Although the model with 5:20:1 had a better R of 99% each in the testing and validation phases. Judging by the MSE and the R metrics therefore, the model with 5:20:1 was selected as the best model. In addition, it is evident from Figure 6 that predicted slump results obtained using ANN with architecture 5:20:1 is the closest to actual slump results. A further confirmation why it recorded the lowest MSE. The NSE values obtained also confirmed that the model with 20 hidden neurons is the most effective model with highest NSE value of 0.96. the Model with 15 hidden neurons recorded NSE of 0.95. 0.01 short of that obtained with 20 hidden neurons. Only the model with 10 hidden neurons fell short of the recommended value by Abdullah (2020) as the model with 5 hidden neurons gave NSE of 0.8. The weights and biases of the chosen network are given in Appendix 1.

Table 3
Performance of Developed Models based on MSE, R and NSE.

Number of Neurons in hidden layer	5	10	15	20	MLR
MSE	0.000519	0.000194	$1.42e^{-22}$	$8.33e^{-27}$	0.83
R	91%	89%	99%	98%	88.86%
NSE	0.8	0.7	0.95	0.96	0.87

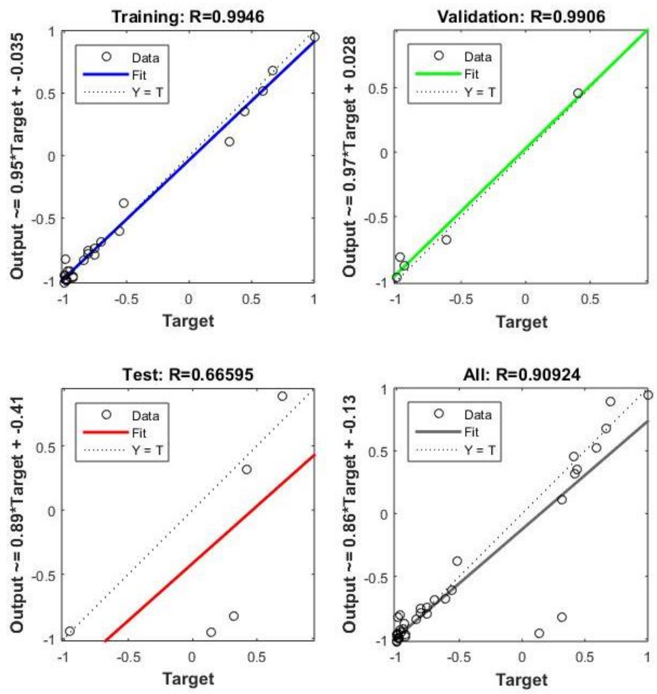

Fig. 7. Performance of 5:5:1 slump model.

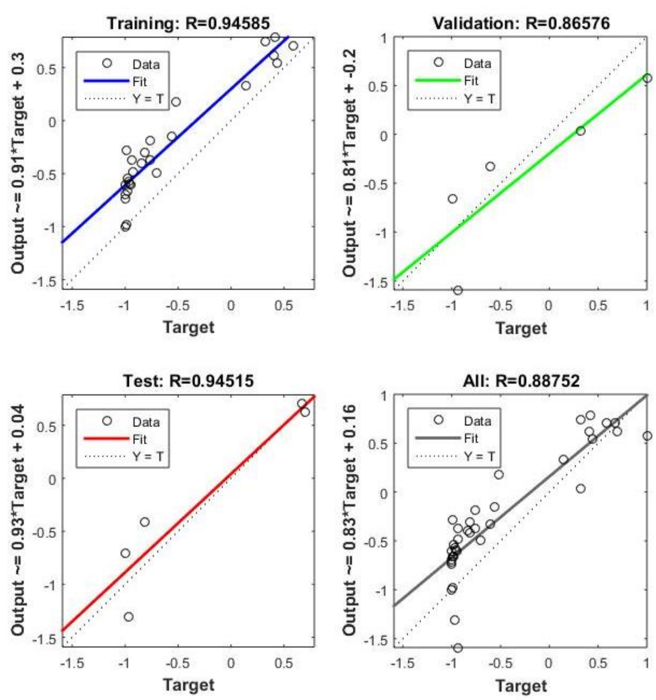

Fig. 8. Performance of 5:10:1 slump model.

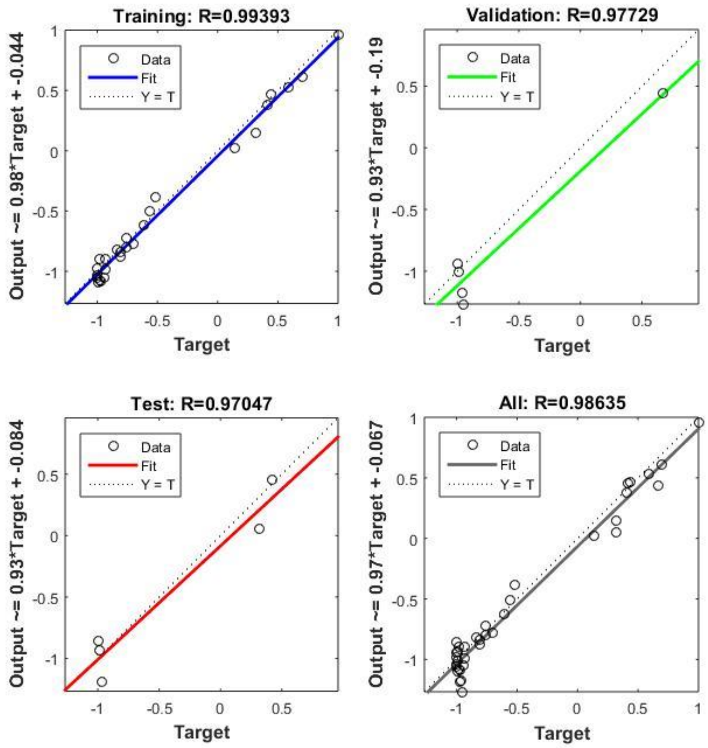

Fig. 9. Performance of 5:15:1 slump model.

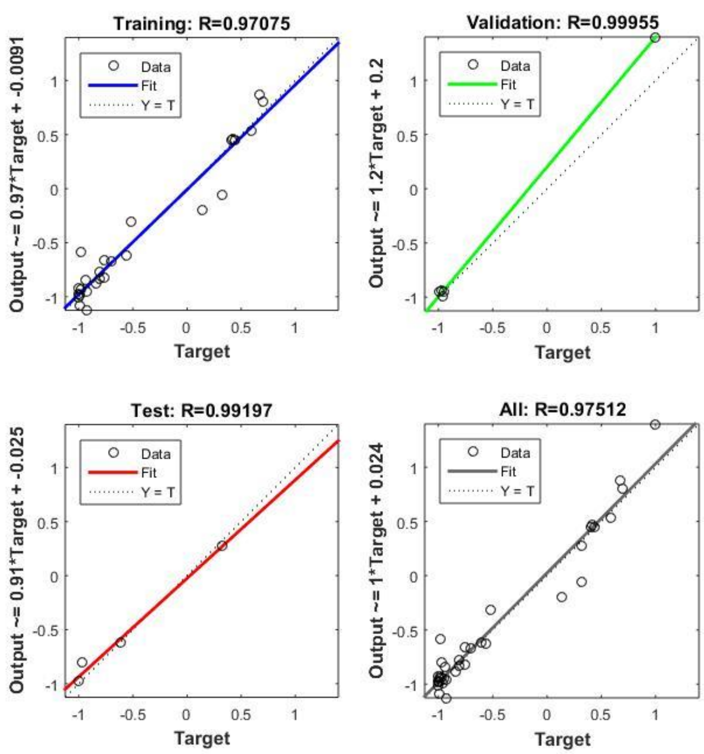

Fig. 10. Performance of 5:20:1 slump model.

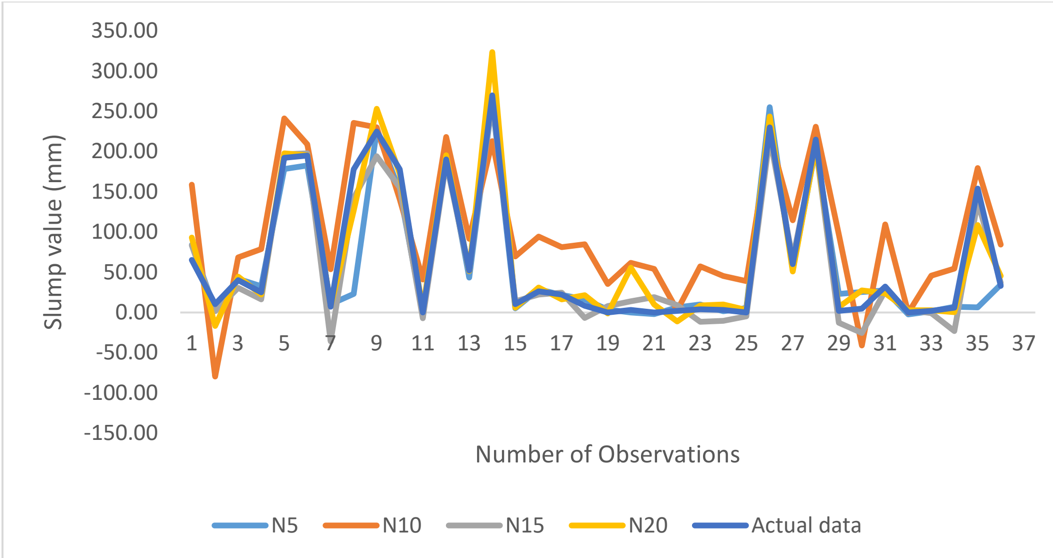

Fig. 11. Actual vs predicted slump for all architecture.

The performance of the best (selected) ANN slump model was further compared with Multiple Linear Regression (MLR) model developed using Minitab software (version 2017) [52] with the intention of validating the selected model. The input parameters used for the ANN model was used as the predictors while slump was used as response variable. The general form of MLR model is given in equation 10 while the developed MLR model is shown in equation 11.

$$MLR = k + \lambda 1x1 + \lambda 2x2 + \cdots + \lambda nxn \tag{10}$$

Where;

k is the intercept (constant)

λ is the coefficient of the predictors x

x is the predictors

n is the number of predictors.

$$\Gamma MLR = 0.29ca + 0.24fa + 6.76w - 1.95c - \frac{1638w}{c} - 122 \tag{11}$$

Where;

ca is the coarse aggregate (BNG) content

fa is the sand content

w is the water content and

c is the cement content all in kg/m^3

The MLR model recorded an MSE of 0.83 and R value of 88.68%. When compared to the selected ANN slump model which recorded MSE of $8.33e^{-27}$ and R value of 98%, it can be deduced that the selected 5:20:1 model had lower MSE and higher R value. Thus, the 5:20:1 model performed better than the MLR model based on the MSE and R performance metrics as it possesses the ability to better fit the predictors to an approximate model estimation with a smaller margin for error. Reduced full quadratic slump model developed by [40] using the same coarse aggregate recorded R value of 93.7%. This clearly attest that ANN provides a more accurate result than statistical models. Figure 8 shows the output of the performance of the selected 5:20:1 slump model and the MLR model which further provides a clear insight of the most fitted model. The 5:20:1 slump model pattern can be observed to be approximately equal to the actual laboratory data which justifies why it recorded a higher R than the MLR model.

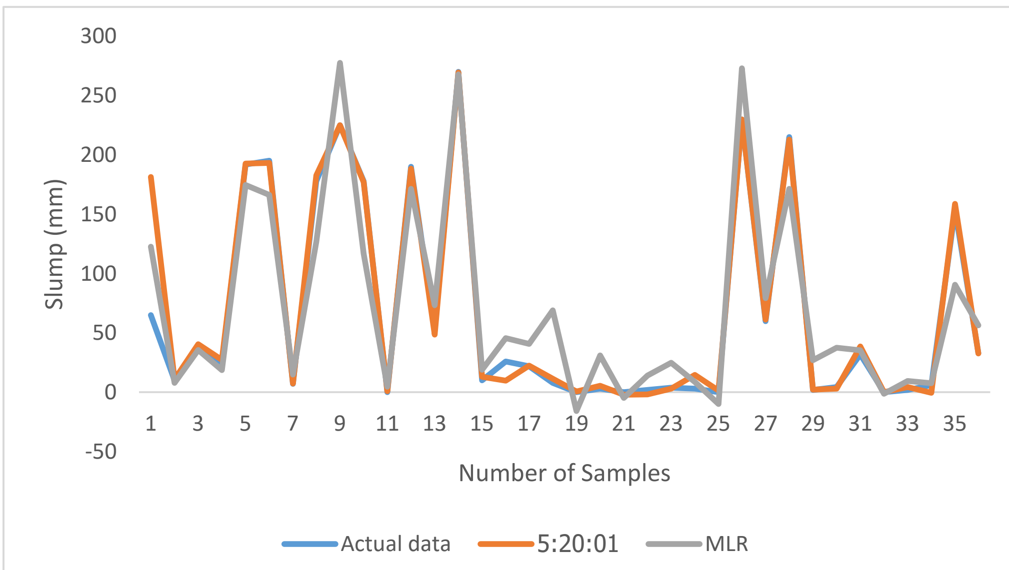

Fig. 12. Performance of selected 5:20:1 slump model vs MLR slump model.

6. Conclusion

From the outcome of the research, the following are the conclusion;

1. The higher the number of hidden neurons in ANN slump model, the better the prediction capacity of the network.

2. ANN architecture with 20 hidden neurons is sufficient in predicting slump of concrete containing BNG based on recorded MSE of $8.33e^{-27}$, R value of 98% and NSE of 0.96.

3. The value from the predicted slump model closely followed the experimental data.

4. ANN is a more powerful concrete slump prediction tool than MLR for BNG concrete.

Appendix 1

Weight to hidden layer [20x5] matrix

[-2.1041 0.11837 -0.33612 1.5324 0.79779;
1.1369 1.5934 -1.1409 0.42989 -0.98786;
-2.0427 0.31961 1.6651 0.37159 -0.24211;
-0.054273 1.5463 -1.7366 1.0523 -0.087478;
-1.0474 -0.10507 -1.5803 0.7239 -1.7708;
1.6404 -0.35768 -0.37887 -1.5718 0.73019;
0.70389 1.1721 -1.1471 -1.4739 -0.93154;
0.083494 -1.6204 0.054682 1.4453 0.049521;
-0.20508 -1.9843 -1.079 -1.4557 0.53514;
-1.2759 -0.74022 1.5473 -1.4435 -0.70703;
1.1126 -0.42375 2.0895 0.68924 -1.474;
-1.3789 1.1178 -1.2836 1.2217 0.2526;
-1.6821 1.2345 0.98699 0.62022 -0.91913;
0.17716 -1.6031 -0.80465 -1.2798 1.2098;
-1.6284 -0.33157 -0.13725 -0.52439 1.7677;
1.8972 0.13238 0.33643 -0.32311 1.5551;
0.68865 -0.64695 1.2957 1.7533 -0.20571;
1.6747 1.2255 -0.21178 -1.7883 0.01738;
-0.89315 0.36088 1.2928 1.2873 -1.2161;
0.78646 -0.93615 -0.90498 0.60564 1.9358]

Weight to output layer [1x20] matrix

[0.3986 0.72687 -0.098535 0.47662 -1.2155 -0.41836 0.31963 -0.7611 -0.76003 -0.40674 -0.46556 -0.12524
0.32159 0.24266 -0.045024 0.14217 -0.22616 -0.6055 -0.29124 -0.2835]

Bias to Hidden Layer [20x1] matrix

[2.0286;
-2.5979;
1.9232;
1.7156;
1.9216;
-1.4309;
-0.89887;
-0.65651;
0.3573;
-0.1768;
-0.064252;
-0.50287;
-0.67805;
1.0572;
-1.1715;
1.5332;
1.6232;
1.7989;
-2.48;
2.5807]

Bias to output layer

[0.81435]

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