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TOPIC:

MODELING COMPRESSIVE STRENGTH OF CONCRETE CONTAINING CRUSHED GLASS AND NATURAL GRAVEL USING ARTIFICIAL NEURAL NETWORK

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ABSTRACT

This research modelled the 28-day compressive strength of concrete containing crushed glass and Bida Natural Gravel (BNG) based on deep learning algorithm using the MATLAB neural network toolbox. A total of 240 (150mm × 150mm × 150mm) cubes were cast from 80 mixes generated randomly using Scheffe's simplex lattice approach. The compressive strength was the mean 28-day strength of three cubes for each of the experimental points. The resulting batch for each mix was used as input data while the laboratory results for compressive strength was the output data for the ANN-model. The developed model will be able to predict the 28-day compressive strength of concrete containing 0% - 25% crushed glass as partial replacement for fine aggregate, water-cement ratio ranging from 0.45 – 0.65 and concrete grade M15 – M25. The architecture of the network contained 6 input parameters: water to cement ratio, water, cement, sand, crushed glass and BNG, 20 neurons in the hidden layer and compressive strength in the outer layer. The performance of the developed model was examined using Mean Square Error (MSE) and Correlation Coefficient (R). Results showed that 6:20:1 model architecture for compressive strength had an MSE values for training, validation and testing are: 0.15, 4.14, 1.15, 0.86 respectively. Regression values for training, validation and testing are: 80%, 65%, 85% and 75%. The study concluded that a shallow Neural Network architecture with 20 neurons in the hidden layer is sufficient for predicting the 28-day compressive strength of concrete.

KEYWORDS

Back Propagation Artificial Neural Network (BP)-ANN; Bida Natural Gravel (BNG); Crushed glass; Mean Square Error (MSE), Regression; Compressive strength.

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1. Introduction

Concrete is a widely used man-made construction material in the world. It is a composite material made from cementitious materials, water, aggregates and additives when required. Cementitious materials and water are combined to create water-cement paste, which coats the surface of both fine and coarse aggregate in a compact mass in addition to filling fine aggregate voids (Gambhir, 2013). Due to environmental and sustainability considerations, by-products such as: fly ash, blast furnace slag, waste plastic, waste glass, rice husk ash, to mention but a few have been used by researchers as admixtures and substitutes in concrete (Saeed *et al.*, 2021;

Kara *et al.*, 2012; Afrifa *et al.*, 2023; Zainab and Enas, 2008; Dhanalakshmi *et al.*, 2023). Typically, these additives are added to concrete to improve workability, compressive strength, flexural strength, etc. Waste glass has grown in popularity as a partial substitute for fine or coarse aggregate in concrete production over the years.

The proportioning of materials that make up concrete and most significantly the water-cement ratio is important in compressive strength development. The slump of a concrete mix and subsequently its strength are influenced by the water to cement ratio as well as other elements which include particle size, shape, and texture. The prediction of compressive strength using mathematical and computational models in accordance with the proportioning design has attracted the interest of researchers who seek to provide solutions to problems relating to cost, time required to determine strength of concrete mixes (Tsivilis *et al.*, 1995; Kheder *et al.*, 2003; Akkurt *et al.*, 2004; Hwang *et al.*, 2004).

2. Artificial Neural Network (ANN) Overview

Artificial neural networks (ANNs) have gained traction in recent years for their use in modelling the mechanical properties of concrete. A set of numerical values that represent a concrete batch containing: water, cement, aggregates, and other admixtures are inputs, and the ANN simulates the compressive strength of the concrete if it is well-trained (Wu, 2021). In modeling complex and non-linear relationship in various components of concrete in many concrete researches, ANN have been successfully deployed in predicting outcomes of these studies. Although, their efficiency depends on the quality of data base used in the training of the models.

Simulation of the compressive strength of concrete using neural networks has been the subject of interest to many researchers. Lin *et al.* (2021) modelled the 28-day compressive strength of concrete using ANN. They implemented the Hao *et al.* (2018) database, which served as the basis for the same application. They assumed that testing was done with insufficient data in Hao *et al.* (2018), which called for additional research on the data set conducted by Lin *et al.* (2021). Hence, Lin *et al.* (2021) remodeled the data by using more data for testing while training the network on fewer data. As a result, despite having just half as many neurons in the hidden layer as the model from Hao *et al.* (2018), the ANN model from Lin *et al.* (2021) performed better.

Hao *et al.* (2018) and Lin *et al.* (2021) developed BP-ANN models, a technique that was adopted in this study. There are numerous ANN varieties in addition to the BP-ANN - Radial Basis Function (RBF) neural network is one of them. In contrast to BP-ANN, the RBF-ANN solution is obtained in a relatively simple manner. For a linear algebraic system with a unique solution, the RBF centres and their form parameters are often defined beforehand, and the weights are subsequently found via the least-squares method (Wu, 2021). For the purpose of forecasting concrete's 28-day compressive strength, Wu (2021) worked on an RBF-ANN model. The database used in his study was a collection of data from other works (Jiang *et al.*, 2000; Demirbo˘ga *et al.*, 2004; Yen *et al.*, 2007; Oner and Akyuz, 2007; Durán-Herrera *et al.*, 2011) to the one used in his previous work. He concluded that the BP-ANN architecture in earlier work was outperformed by the current RBF-ANN model.

3. Materials and Methods

3.1. Materials

Materials used for this research work are; sand, cement, Bida gravel, water and waste glass. Ordinary Portland Cement grade 42.5N (Normal hardening and 28-day compressive strength of 42.5 N/mm^2) was used for this research. Fine aggregate was sourced from Minna area of Niger state. Bida gravel was gotten from Bida area in Niger state. The gravel was washed in 5mm British Standard sieve to remove clay impurities which may affect concrete production and dried. Portable water was gotten from the civil engineering laboratory. The water used was colourless, odourless and free from visible impurities in accordance with BS EN 1008:2002. Waste glass was sourced from the mechanical engineering central workshop at the Federal University of Technology, Minna.

Figure 1: Sample of the crushed glass

Figure 2: Sample of Bida Natural Gravel (BNG)

Table 1: Physical properties of the aggregates

Physical Properties	Materials		
	Sand	**CG**	**BNG**
Fineness Modulus	2.7	2.5	6.4
Absorption (%)	2.68	2.60	2.37
Specific gravity	2.6	2.51	2.68
Density (kg/m^3)	1515	1453	1663
AIV (%)	-	-	16.56

Note: CG – Crushed glass; BNG – Bida Natural Gravel; AIV: Aggregate Impact Value

3.2. MATLAB neural network toolbox

The MATLAB software has a Neural Network (NN) toolbox. It is a technical computing language with great performance. In a simple-to-use environment, it mixes computing, visualization, and programming while expressing issues and solutions using well-known mathematical notation. MATLAB software (version R2022b) was deployed to develop a back propagation neural network technique in this study.

3.3. Methods

3.3.1. Concrete mix

For the model's training, testing, and validation, a total of 240 (150 × 150 × 150 mm) concrete cubes were produced. 80% of the data was arbitrarily chosen and utilised for training, 15% for validation, and 5% for testing. Using the simplex lattice strategy developed by Scheffe (1958), 80 experimental mix combinations were produced. The contents of water, cement, sand, and BNG were then determined in kg/m^3 using the absolute volume method. In modelling the compressive strength of concrete, the water-cement ratio (w/c), cement, sand, crushed glass, and BNG content were passed into the artificial neural network (ANN) as input data, and the average compressive strength test results obtained from three (3) trial mixes for 80 experimental points were passed into ANN as output data.

3.3.2. Developing the feed forward neural network

The following variables were the input data, while creating the neural network: water-cement ratio (W/C), weight of water (W), weight of cement (C), weight of sand (S), weight of crushed glass (CG), the weight of BNG. Several batches of concrete mixes were used to ascertain their impact on the strength of the concrete. From the mix design, the range of constituent materials was calculated. Additional parameters such as: number of hidden layers, number of neurons in hidden layers, and learning rate were determined while the model was simulated.

$$(net)_j = \sum_{i=1}^{n} w_{ij} x_i + b \tag{1}$$

Where (net)j is the weight of the j neuron for the input received from the preceding layer with n-neurons, wij is the weight between the j-neuron in the preceding layer, xj is the output of the i- neuron in the preceding layer (Pala et al., 2007), b is a constant which is referred to as the bias and ∑ represents sum function.

$$(out)_j = f(net)_j = \frac{1}{\left(1+e^{-\alpha(net)j}\right)} \tag{2}$$

Where, α is a constant which is used to control the slope of the semi-linear region. The sigmoid nonlinearity activates in every layer except in the input layer (Kewalranmi et al., 2006).

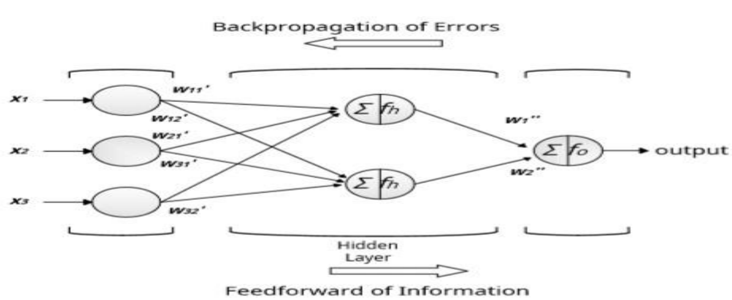


Figure 3: Back propagation and forward propagation (Constantinou, 2017)

4. Results and Discussion

4.1. Compressive strength

The compressive strength of a concrete is the maximum axial compressive load it can withstand before failure. It is a measure of strength and a useful parameter in the structural design of concrete structures. The laboratory results are the features from which the ANN model for 28-day compressive strength was developed. Water to cement ratio, water, cement, sand, crushed glass and BNG content served as input for the feed-forward network while compressive strength was the output from the network. The compressive strength of concrete cubes for the 80 experimental points at 28-day curing of the hardened concrete is presented in Appendix A.

4.2. ANN model

The model for 28-day compressive strength was trained with a shallow neural network in the MATLAB neural network toolbox. A shallow network is a multi-layer supervised learning network with one hidden layer. In supervised learning, the weights associated with each neuron in each layer are initialized and activated with an activation function before it is fed to another neuron in the next layer. This is called the feed forward network. At the output layer, the error associated with the feed-forward network is calculated. To minimize this error and improve on the accuracy of the network, the weights are adjusted using techniques such as: stochastic gradient descent, batch method and the mini-batch method. This process is referred to as backward propagation. In this study, the stochastic gradient descent technique was adopted. The network architecture was made of 80 observations, 6 features in the input layer 1, 20 neurons in the hidden layers and 1 feature in the output layer of the network. The parameters used in training the models are presented in Table 2.

Table 2: Training parameters for the ANN model

Parameter	Configuration
Input Data	w/c, water, cement, sand, crushed glass and BNG
Output Data	Compressive strength
Maximum number of Epochs	1000
Validation Checks	6
Target Gradient	1×10^{-7}
Training Algorithm	Levenberg-Marquardt
Activation Function	Hidden layer – Sigmoid; Output layer – Linear
ANN Architecture	6 : 20 : 1
Performance Check	Mean Square Error (MSE) and Regression

Figure 4 shows the network architecture of the models. Six (6) input data: water to cement ratio, water, cement, sand, crushed glass and BNG content were passed to the network as input and the 28-day compressive strength was the response for the output layer. A total of 80 observation points were used to train the network. 80% of the data were used to train the network, 15% were used for validation and 5% were used for testing. Additional 42 secondary data synthesized from the laboratory results were used to further test the network.

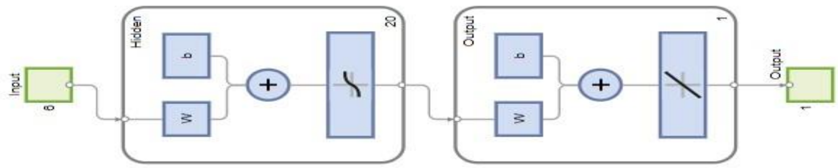


Figure 4: Network architecture of the shallow neural network model

Table 3: Training result based on Mean Square Error (MSE) and Regression (R)

	Observation	MSE	R
Training	64	0.15	0.8
Validation	12	4.14	0.65
Test	4	1.15	0.85
Additional Test	42	0.86	0.75

The performance of the model based on MSE and Regression is presented in Table 3. The MSE values for training, validation and testing are: 0.15, 4.14, 1.15, 0.86 respectively. Regression values for training, validation and testing are: 80%, 65%, 85% and 75%. The regression values imply that the model is quite satisfactory. Regression plots based on the training, validation and testing of data are presented in Appendix B.

5. Conclusions

The architectural design of the neural network, consisting of six input parameters and a hidden layer with 20 neurons, demonstrated robust performance. The assessment metrics, including Mean Square Error (MSE) and Correlation Coefficient (R), confirmed the model's accuracy and reliability. Notably, the 6:20:1 model architecture yielded favorable MSE values during training, validation, and testing, reinforcing its effectiveness in predicting compressive strength.

This study concludes that a shallow neural network architecture with 20 neurons in the hidden layer is a suitable and efficient approach for accurately forecasting the 28-day compressive strength of concrete in diverse compositions, thereby contributing valuable insights to the field of construction materials and engineering. This research has the potential to reduce the time designers and likes use in modelling mixes for concrete production as well structural engineers who need to predict concrete strength for use in structural designs. This will further save cost and increase delivery rate of projects in the construction industry.

In conclusion, the exploration of trends in sustainable civil infrastructure development for economic growth underscores the critical importance of aligning our construction practices with the principles of sustainability. As our global population continues to expand, and urbanization accelerates, the demand for infrastructure that supports economic growth remains paramount.

The trends highlighted in this study, ranging from green building technologies to resilient infrastructure design and data-driven decision making system using Artificial Intelligence (AI), collectively demonstrate a paradigm shift in the way we approach civil engineering and construction. These trends not only foster economic growth but also promote eco-friendliness and sustainability.

Appendices

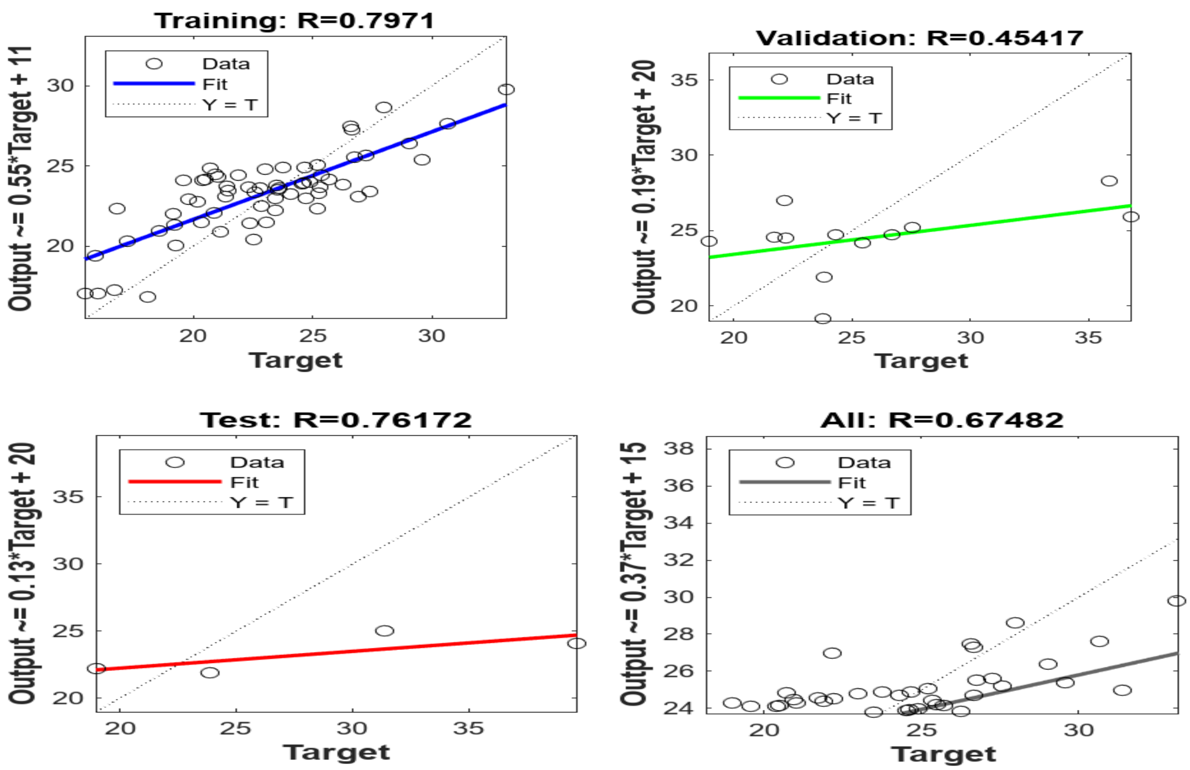
Appendix A: 28-day compressive strength Concrete

S/N	W/C	Water (kg)	Cement (kg)	Sand (kg)	Crushed Glass (kg)	BNG (kg)	Compressive Strength (N/mm^2)
1	0.45	1.61	3.58	7.32	0.39	16.41	18.09
2	0.50	2.84	5.68	5.5	0.61	13.02	22.37
3	0.78	3.35	4.27	5.87	1.04	14.69	15.45
4	0.60	2.06	3.43	5.9	1.48	15.7	15.91
5	0.65	2.68	4.13	5.55	1.11	14.18	25.26
6	0.66	2.9	4.39	6.62	0.47	15.1	18.98
7	0.52	2.56	4.88	5.71	0.85	13.97	26.74
8	0.58	2.19	3.8	5.89	1.28	15.25	25.47
9	0.63	2.34	3.74	5.74	1.31	15.01	25.19
10	0.55	2.11	3.83	6.5	0.72	15.38	22.52
11	0.50	1.95	3.9	6.66	0.68	15.63	26.59
12	0.58	2.75	4.78	5.53	0.9	13.69	20.16
13	0.55	2.35	4.27	5.75	1.15	14.69	20.39
14	0.53	1.84	3.5	6.6	0.94	16.05	21.36
15	0.60	2.52	4.2	5.71	1.07	14.43	19.20
16	0.51	2.1	4.09	6.56	0.61	15.25	25.19
17	0.50	2.31	4.62	6.19	0.65	14.57	20.93
18	0.59	2.23	3.79	6.12	1.02	15.19	27.56
19	0.55	2.35	4.27	5.81	1.09	14.69	20.49
20	0.60	2.26	3.77	5.81	1.29	15.19	22.84
21	0.52	2.4	4.58	6.1	0.68	14.43	26.90
22	0.49	2.01	4.13	6.64	0.58	15.38	30.67
23	0.51	2.22	4.33	6.18	0.82	14.89	35.85
24	0.50	1.95	3.9	6.61	0.73	15.63	28.00
25	0.56	2.39	4.26	6.07	0.8	14.63	23.48
26	0.54	1.97	3.66	6.55	0.84	15.73	23.81
27	0.57	2.3	4.01	6.12	0.89	14.93	27.26

28	0.55	2.66	4.83	5.62	0.88	13.83	25.29
29	0.54	2.45	4.56	5.73	1.01	14.36	19.79
30	0.56	2.54	4.51	5.71	0.97	14.22	21.70
31	0.54	2.07	3.85	6.27	0.98	15.44	21.42
32	0.56	2.26	4.03	5.82	1.22	14.99	29.57
33	0.59	2.35	3.99	5.8	1.18	14.86	23.44
34	0.61	2.42	3.96	5.73	1.2	14.74	18.58
35	0.57	2.08	3.62	6.18	1.12	15.55	26.67
36	0.54	2.31	4.29	6.15	0.78	14.76	19.59
37	0.56	2.15	3.82	6.19	1	15.32	31.41
38	0.55	2.22	4.04	6.15	0.92	15.05	18.96
39	0.58	2.44	4.24	5.73	1.11	14.56	24.89
40	0.52	2.14	4.08	6.23	0.91	15.18	22.15
41	0.59	2.32	3.91	5.79	1.23	14.95	16.79
42	0.54	2.33	4.28	5.8	1.11	14.72	23.56
43	0.56	2.07	3.69	6.3	0.99	15.52	22.58
44	0.53	2.27	4.31	6.26	0.7	14.81	24.53
45	0.50	2.16	4.36	6.38	0.66	14.99	29.04
46	0.53	1.97	3.73	6.4	0.97	15.68	21.90
47	0.58	2.44	4.23	5.69	1.14	14.55	23.61
48	0.55	2.17	3.98	6.32	0.82	15.19	27.41
49	0.51	2.06	4.02	6.35	0.87	15.36	33.11
50	0.56	2.59	4.61	5.66	0.95	14.08	25.36
51	0.65	2.20	3.38	6.91	0.36	15.48	16.71
52	0.55	3.05	5.55	5.37	0.60	12.71	16.03
53	0.60	2.52	4.20	5.76	1.02	14.43	23.44
54	0.45	1.61	3.58	6.17	1.54	16.41	26.67
55	0.50	2.18	4.35	5.86	1.17	14.96	24.67
56	0.60	2.52	4.20	6.33	0.45	14.43	25.69
57	0.63	2.34	3.74	6.40	0.65	15.01	21.13
58	0.55	1.91	3.48	6.55	0.94	15.93	23.78
59	0.58	2.19	3.80	6.45	0.72	15.25	17.24
60	0.58	2.75	4.78	5.60	0.84	13.69	21.48
61	0.50	2.18	4.35	5.86	1.17	14.96	23.76
62	0.53	2.56	4.88	5.64	0.92	13.97	22.99
63	0.53	2.03	3.87	5.98	1.30	15.50	19.16
64	0.55	2.35	4.27	5.81	1.09	14.69	39.63
65	0.48	1.87	3.93	6.03	1.37	15.76	36.81
66	0.56	2.04	3.63	6.50	0.83	15.61	19.29
67	0.55	2.35	4.27	6.10	0.81	14.69	22.79
68	0.51	2.10	4.09	5.92	1.24	15.25	23.04
69	0.53	2.03	3.87	6.24	1.04	15.50	22.21
70	0.54	2.18	4.06	5.90	1.20	15.12	24.07
71	0.59	2.50	4.21	6.15	0.64	14.46	20.33

72	0.56	2.07	3.69	6.33	0.96	15.52	24.74
73	0.54	2.17	3.98	6.28	0.86	15.19	24.64
74	0.53	2.27	4.31	5.84	1.12	14.81	20.87
75	0.58	2.27	3.93	6.25	0.81	15.03	21.04
76	0.56	2.26	4.03	6.15	0.89	14.99	20.73
77	0.53	2.26	4.31	5.83	1.13	14.83	23.85
78	0.55	2.11	3.83	6.22	1.01	15.38	22.30
79	0.54	2.18	4.06	6.17	0.93	15.12	24.30
80	0.58	2.44	4.24	6.07	0.77	14.56	26.27

Appendix B: Regression Analysis for training, validation and testing of compressive strength model



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