

Predicting the Modulus of Elasticity of Recycled Aggregate Concrete Using an Artificial Neural Network Model in The Gambia

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Abstract— Recycling construction and demolition waste is essential in reducing its environmental impacts such as occupied land space and the leaching of harmful substances into the underlying soil. Understanding the mechanical properties of such waste ensures the strength and quality of concrete with recycled waste aggregates are not compromised. This study is divided into two components. The experimental component compared the compressive strength and elastic modulus of natural aggregate concrete (NAC) with that of recycled aggregate concrete (RAC). The RAC consisted of natural coarse aggregates replaced 100% by recycled concrete aggregates (RCAs) and was seen to do just as well as the NAC, showing that RAC is a viable option for structural use. In the artificial neural network (ANN) development component, the network model was trained using a dataset sourced from about 90 previous studies and used to predict the elastic modulus of RAC. With a mean absolute error (MAE) of 2.23, this study concludes that ANNs can be used to successfully predict mechanical properties of structural concrete.

Keywords— Recycled Concrete, Recycled Aggregate, Modulus of elasticity, Artificial Neural network.

I. INTRODUCTION

The Elastic Modulus (E) is an important mechanical property of materials universally defined as the ratio of stress to strain below the proportional limit. Greater values of elasticity, E, imply smaller strains resulting from larger stresses and, in concrete, indicate greater stiffness or more strength [1]. The elastic modulus of concrete, E_c , is not easily determined as concrete is not an elastic material and does not follow Hooke's law. E_c must be determined in designing structures as it shows the ability of concrete to withstand stresses and not deform elastically, that is, undergo deflections, or produce strains [2, 3]. E_c is also needed to satisfy requirements of ultimate and serviceability limit states [1]. Determining the elastic modulus of concrete involves using a Universal Testing Machine (UTM) or a Compression Testing Machine, and using the compressive strength, C_s , and/or stress-strain graph obtained, to calculate E_c . (Compressive strength is a measure of the compressive forces or loads a material can bear before cracking or fracturing.) This is a tedious, time-consuming process and is not always accurate as there are many formulas available to use [3].

As buildings age, they get to a point where they are deemed unsafe and demolished. Structures may also be demolished for other reasons and this demolition produces construction waste. To catapult into a more environmental and economic industry, the Gambian construction industry can look into how recycled aggregates (RAs) from construction waste can be reused in new upcoming projects/buildings, especially Recycled Concrete Aggregates (RCA). This RCA is derived by separating concrete

rubble from the mortar content, rubble, bricks, tiles, sand, dust, timber, plastics, metals, cardboard, and paper, of construction and demolition waste, and crushing it to required sizes [4]. Determining the Ec of concrete made with RCAs proves to be a difficult task as RCAs are sourced from different places and the properties of the original concrete are not always known. As the world becomes more aware and concerned about our environment, reusing RAs helps to reduce the number of debris and construction waste that takes up land space and leaches into the ground, making it agriculturally unusable even in the event of a transfer of materials in the future [5]. Environmental risks of RA causing pollution include Chromium (Cr) leaching.

In the past decade, the advancement of Artificial Intelligence (AI) has been useful in application to various human problems, including civil engineering ones. Data-Driven Models (DDMs) are heuristic techniques that have been employed in the concrete industry and successfully predicted the mechanical properties of several types of concrete. Artificial Neural Networks (ANNs) have been particularly outstanding in predicting these properties as compared to other DDMs such as Multivariate Adaptive Regression Splines (MARS), Grasshopper Optimisation Algorithm (GOA), Extreme Learning Machine (ELM), Random Forest (RF), M5 Prime Model Tree (M5p), etc. [6]. ANNs are also much simpler to use. ANNs may be defined as computational models that can perform pattern recognition and retention of information-based knowledge by imitating brain activity. The brain is a complex organ; ANNs run a simplified version of its operations. Thus, ANNs are made up of an input layer, one or more hidden layers, and an output layer. Each layer can have a different number of nodes (i.e., artificial neurons) [7].

It is important to understand the mechanical properties of recycled aggregate concrete (RAC) in reusing it in the construction industry to ensure the quality of buildings produced is not affected by the replacement. The elastic modulus of concrete is one of the most important mechanical properties. Thus, this study seeks to accurately predict the elastic modulus of Recycled Aggregate Concrete in The Gambia using an ANN model, and this is achieved by predicting the compressive strength of Recycled Aggregate Concrete (RAC) in The Gambia, comparing the compressive strength of the Natural Aggregate Concrete (NAC) with that of RAC, comparing the elastic modulus of NAC with that of RAC and predicting the applicability of ANNs in solving further problems within the civil engineering field.

Several RAs have been used to replace natural aggregates (NAs) in concrete mixes such as recycled mortar, recycled bricks, etc. This study limits itself to the use of Recycled Concrete Aggregates (RCAs). The RCAs replaced 100% of the NAs in the experimental component of the study as coarse aggregates for the RAC mix. Fine Aggregates were not replaced in the study and all mixes were designed for normal-weight concrete. The ANN for the study was constructed only for the RAC using TensorFlow [8], Keras API [9], and run on Google Colab [10]. About 90 papers from previous studies were sourced manually in compiling the dataset for the model. The output parameter considered was the elastic modulus of RAC and the study's dataset had a total of 11 input parameters which did not include factors such as the type/nature of curing, the type of natural aggregate, and the moisture state of the RCA.

II. MATERIALS AND METHODS

In carrying out this research, the mix proportions were designed for normal-weight concrete consisting of cement (C), coarse aggregate (CA), fine aggregates (FA), and water (W). The mix proportions are shown in Table 1 below with a target strength of 25–30 MPa:

TABLE 1
CONCRETE MIX PROPORTIONS

Mix ID	C (kg/m ³)	W (kg/m ³)	FA (kg/m ³)	NA (kg/m ³)	RA (kg/m ³)
NAC	300	165	580.5	1354.5	0
RAC	300	165	580.5	0	1354.5

(C: Cement, W: Water, FA: Fine Aggregates, NA: Natural Coarse Aggregates, RA: Recycled Coarse Aggregates)

Additional water (about 500 ml) was added to the recycled aggregate mix (RAC) for better workability. No admixtures were added to either mix. Mixing of concrete, casting of cubes and crushing of cubes is as shown in Figures 1–7 below.



FIGURE 1: Crushing of RCA



FIGURE 2: Mixing of NA



FIGURE 3: NAC and RAC casted in moulds



FIGURE 4: Casted cubes after 24 hours

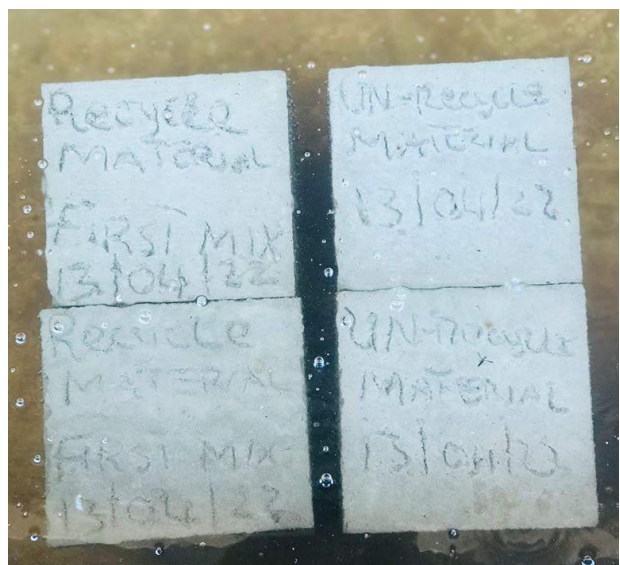


FIGURE 5: Cubes in curing tank



FIGURE 6: Cube being weighed



FIGURE 7: Crushing of cube in the Compressive Testing Machine

Mix Components:

- **Cement:** Salam cement, 42.5N.
- **NA:** Basalt imported from Senegal of particle size gradation, 8/16.
- **RA:** Demolished concrete taken from a Construct Ltd. site located in Bijilo, The Gambia.
- **FA:** Beach sand.

Mixes were filled into prepared cube moulds in three layers and given 25 blows per layer. The cubes were left to solidify for 24 hours (1 day), before they were removed from the mould and placed into the curing tank.

The cubes casted were tested at 7, 14, 21 and 28 days and their respective compressive strengths were determined utilizing a compressive testing machine and Universal Testing Machine (UTM) in the laboratory of National Roads Authority (NRA), The Gambia.

The Compressive Strength Test is a "mechanical test measuring the maximum amount of compressive load a material can bear before fracturing. The test piece, usually in the form of a cube, prism, or cylinder, is compressed between the platens of a compression-testing machine by a gradually applied load" [11].

The compressive strengths obtained were used to determine the elasticity of the mixes using established formulae from BS 8110-2:1985 [12] for normal-weight concrete:

$$\varepsilon_c = 4700\sqrt{f_{cu}} \quad (1)$$

$$\varepsilon_c = k_o + 0.2f_{cu_{28}} \quad (2)$$

Where:

ε_c is Elastic Modulus of Concrete

f_{cu} is Compressive Strength of Concrete

$f_{cu_{28}}$ is Compressive Strength of Concrete at Twenty-Eight Days

k_o is A constant closely related to the modulus of elasticity of the aggregate (taken as 20 kN/mm² for normal-weight concrete)

2.1 ANN Development Component

The ANN for this study was set up once all experimental work had ended. The network was built using the Keras API with TensorFlow [8, 9], on the Google Colab development environment [10]. This was preferred to other options such as MATLAB

[13] because Keras is a deep-learning API run in the background by Python and is simple, flexible and powerful. TensorFlow is also particularly focused on training deep neural networks. An additional advantage is that the combination of this software can be run on the web. A classification of studies done on RAC showed that many authors' studies were limited to the Cs of concrete and did not venture further into Ec [14]. Considering that Ec varies with equations of different standards [15], it was a tough task to find enough concrete data with Ec values. As such, two ANN models were developed to predict the compressive strength and elasticity of concrete respectively.

The data for our models were compiled manually and sourced from about 90 studies/papers [4, 15-22].

TABLE 2
DATASET RANGE OF VARIABLES

Parameter	Input/Output	Unit	No. of App. (801)	Min	Max	Average
Water-to-Cement Ratio (W/C)	Input	–	649	0.25	0.75	0.48
Water (W)	Input	Kg/m ³	755	3	262	183.2
Cement (C)	Input	Kg/m ³	801	6	864	378.87
Sand / Fine Aggregate (FA)	Input	Kg/m ³	781	12	1172	702.24
Natural Aggregate (NA)	Input	Kg/m ³	585	9.6	2860	740.56
Recycled Aggregate (RA)	Input	Kg/m ³	622	2.4	2230	642.16
Rubber	Input	Kg/m ³	3	39.8	79.6	59.7
Steel Fibre	Input	Kg/m ³	3	19.9	39.8	29.87
Silica Fume (SF)	Input	Kg/m ³	47	17.5	89	46.52
Fly Ash (FA)	Input	Kg/m ³	96	18	227.5	114.87
Limestone Powder	Input	Kg/m ³	10	166	370.2	276.08
Superplasticizer (SP)	Input	Kg/m ³	326	0.096	90.23	4.32
Compressive Strength (fcu)	Output	MPa	801	6.7	108.51	41.92
Elastic Modulus (E)	Output	GPa	463	8.69	50.41	28.93

(No. of App.: Number of appearances)

In ANN I, a total number of 801 data entries included 12 input parameters: water-to-cement ratio, water (kg/m³), cement (kg/m³), sand/fine aggregate (kg/m³), natural aggregate (kg/m³), recycled aggregate (kg/m³), rubber (kg/m³), steel fibre (kg/m³), silica fume (kg/m³), fly ash (kg/m³), limestone powder (kg/m³), and superplasticizer (kg/m³); and an output one: compressive strength (MPa). The range of variables of both datasets are shown in Table 2.

In ANN II, a total number of 463 data entries included 11 input parameters: water-to-cement ratio, water (kg/m³), cement (kg/m³), sand/fine aggregate (kg/m³), natural aggregate (kg/m³), recycled aggregate (kg/m³), silica fume (kg/m³), fly ash (kg/m³), limestone powder (kg/m³), superplasticizer (kg/m³), and compressive strength (MPa); and an output one: the elastic modulus of concrete (GPa).

The networks' architecture and parameters are described in Table 3. Forward-feed, back-propagation networks were developed. This type of network determines the difference between processed output and target output to give an error. It then proceeds to adjust the weights itself taking into account the error it generated. It continues to adjust weights until the error generated is insignificant, that is, the processed output is pretty close to the target output. The weights used at that point are stored as the correlation values. Most of the input data had correlation values of less than 0.5 between themselves and the output values, calculated using Spearman's rank correlation coefficient formula (Equation 3). Those with correlation values greater than that were not excluded from the dataset as they did not outright affect the model's performance.

$$\rho = 1 - \frac{6\epsilon d^2}{n(n^2-1)} \quad (3)$$

ρ — Spearman's Rank Correlation Coefficient

d — Difference between the Two Ranks of each Observation

n — Number of Observations

TABLE 3
ANN ARCHITECTURE AND PARAMETERS

Parameter	ANN I	ANN II
Architecture	12-4-2-1	11-4-2-1
Number of Input Layers	1	1
Number of Input Nodes	12	11
Number of Hidden Layers	2	2
Number of Hidden Nodes (i.e., Weights)	4, 2	4, 2
Number of Output Layers	1	1
Number of Output Nodes	1	1
Momentum Rate	0	0
Learning Rate	1×10^{-4}	1×10^{-4}
Epochs	150	150
Dataset Shape	(801,13)	(463,12)

Figures 8 and 9 below show flowcharts of the ANNs adopted:

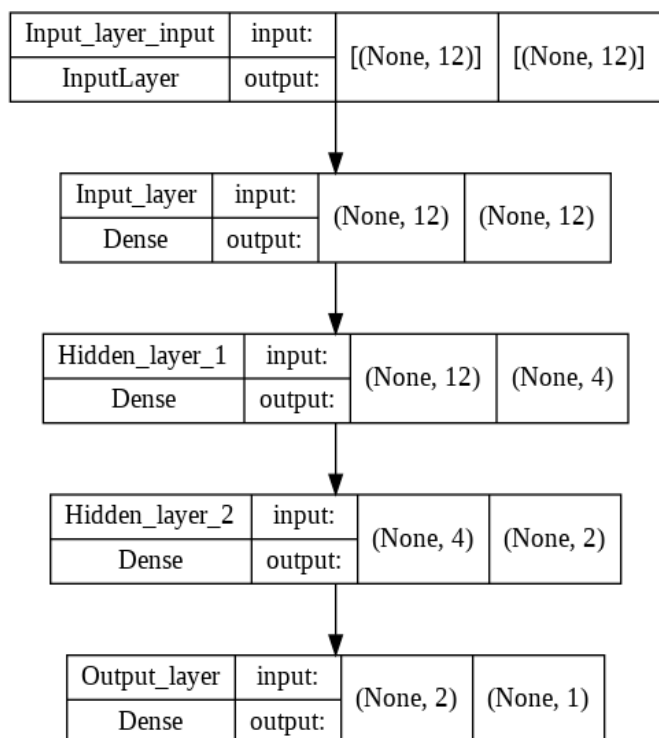


FIGURE 8: ANN I flowchart

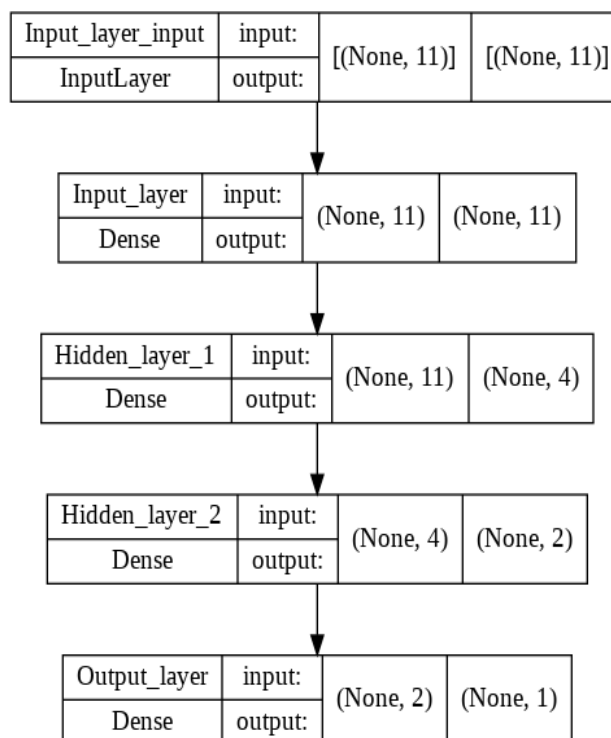


FIGURE 9: ANN II flowchart

The datasets were divided into two for training and subsequent testing. Approximately 14% of the data was kept for validation of the model whilst the remaining 86% was used in training. Additionally, the input parameters data was normalised in rescaling it for better learning.

III. RESULTS AND DISCUSSION

As seen in Table 4, the compressive strength of the cubes attained for both RAC and NAC were not up to standard. Even more surprisingly, the RAC was stronger than the NAC (Figure 10), which does not conform to trends in the large majority of previous studies [16, 20, 21, 22], although a few studies show results with RAC stronger than NAC even without the addition of superplasticizers, especially with differing coarse aggregate replacement percentages and water-to-cement ratios [17, 20].

TABLE 4
COMPRESSIVE STRENGTH RESULTS

Cube ID	Curing Time	Cast Date	Test Date	A (mm ²)	W (g)	L (KN)	fcu (MPa)	fcu Avg. (MPa)
Natural Aggregate Samples								
NAC1	7 days	13-04-2022	20-04-2022	22500	8661	119.2	5.3	5.9
NAC2					8263	144.7	6.4	
NAC3	28 days	13-04-2022	11-05-2022	22500	8548	233.1	9.1	9.7
NAC4					8495	229.3	10.2	
Recycled Aggregate Samples								
RAC1	7 days	13-04-2022	20-04-2022	22500	8065	174	7.7	8.9
RAC2					7593	228.3	10.1	
RAC3	28 days	13-04-2022	11-05-2022	22500	7738	308.2	13.7	13.9
RAC4					7834	317.3	14.1	

(A: Cube Surface Area, mm²; W: Weight, g; L: Load at Failure/Cracking, KN; fcu: Compressive Strength, MPa)

Where the water-to-cement ratio of the RAC is lower than that of the NAC, the compressive strength of the RAC can be equal to or even higher than that of the NAC. However, it is more common for RAC compressive strength to be 10–25% lower than that of similar NAC [4].

The observed comparable strength between the two mixes can be attributed to a number of reasons: Firstly, the composition of the original concrete recycled as RCA is not known – it may have possessed superplasticizer or other concrete enhancing admixtures. Secondly, it would be expected that the total porosity of the RAC would be more than that of the NAC [19]. However, considering that the RCA in this study did not undergo a particle size distribution, there is the likelihood that the fines present in the RCA filled up pore spaces in the RAC mix thus reducing its porosity and giving it similar strength to the NAC. Finally, the cement brand used in the original concrete for the RCA may have been 'GACEM' or 'Tiger Cement', which could be of higher grade than the cement used in this study (Salem cement). This may also be responsible for the overall low strength results in both of the mixes.

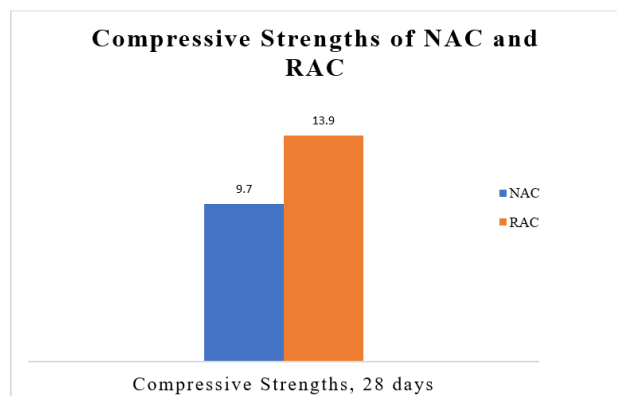


FIGURE 10: Comparison between Experimental Compressive Strengths of NAC and RAC

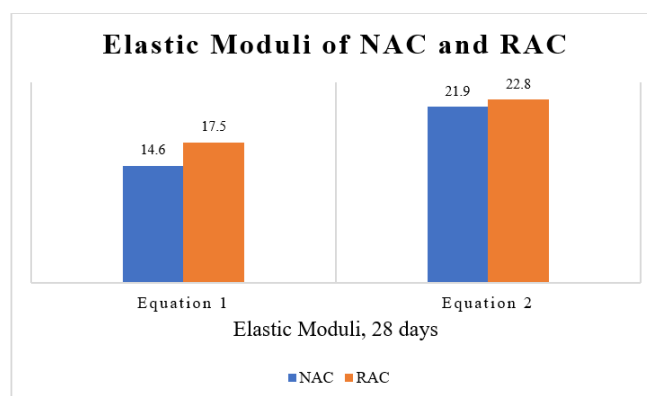


FIGURE 11: Comparison between Elastic Moduli of NAC and RAC

Similarly, the elastic moduli of the RAC were higher than the NAC using both Equations 1 and 2, as seen below in Figure 11.

3.1 ANN Results

Losses that arose in the training of ANNs were expressed as mean squared errors (MSEs) which can be calculated using Equation 4 below. Table 5 shows the performance of the ANN models: their losses and mean absolute errors (MAEs). The formula for the generation of MAEs is shown in Equation 5.

$$MSE = \frac{1}{n} \sum \varepsilon (y - y')^2 \quad (4)$$

$$MAE = \frac{1}{n} \sum \varepsilon |y' - y| \quad (5)$$

Where:

MSE is Mean Squared Error

MAE is Mean Absolute Error

n is Number of Data Points

y is True / Observed Values

y' is Predicted Values

TABLE 5
PERFORMANCE OF ANN MODELS

Results	Training Loss	Training MAE	Validation Loss	Validation MAE
ANN I	95.07	7.46	109.61	7.98
ANN II	14.24	2.7	9.84	2.23

In general, the closer the losses and MAE values are to zero (0), the better the performance of a model, although this is also dependent on the size of the dataset and other properties of the model. As such, our models' performances were acceptable as seen in Table 5.

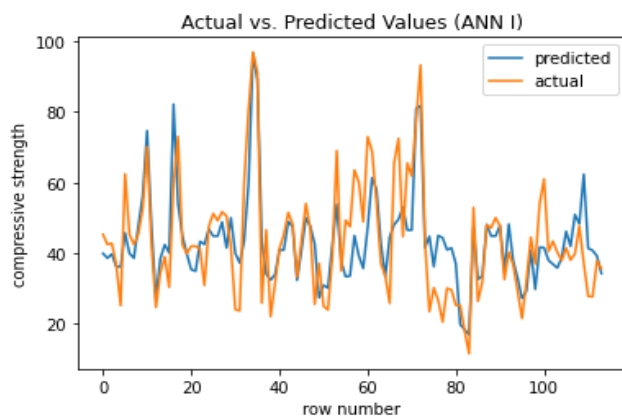


FIGURE 12: ANN I – Actual vs. Predicted Cs Values

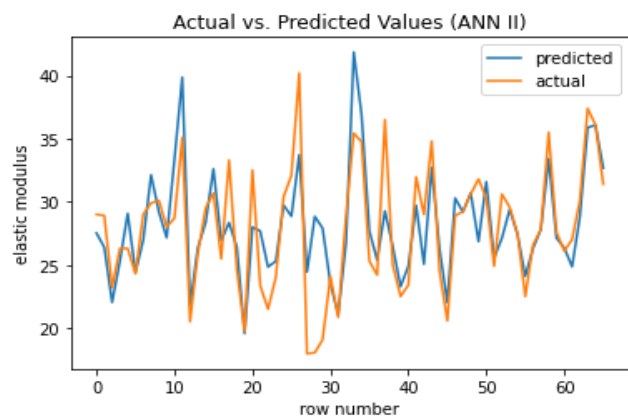


FIGURE 13: ANN II – Actual vs. Predicted Ec Values

Figures 12 and 13 show comparisons between the actual values of the Cs and Ec of models I and II and the predicted values using the validation dataset. The graphs clearly show that the predictions were mostly similar. The model was also able to accurately predict the compressive strength and elastic modulus of RAC and the RAC mix in the experimental component of this study. Table 6 compares the predicted values with those determined experimentally and shows the error percentage of the results calculated using Equation 6.

$$Error (\%) = \left| \frac{\text{predicted value} - \text{actual value}}{\text{actual value}} \right| \times 100 \quad (6)$$

The predicted results for the RAC mix show that the experimental results were subpar as concluded above, particularly the compressive strength.

TABLE 6
EXPERIMENTAL RESULTS COMPARED WITH PREDICTED ANN RESULTS

Mix ID	Experimental Results [†]		Predicted Results by ANN Model			
	F _{cu} (MPa)	E _c (GPa)	F _{ANN} (MPa)	Error (%)	E _{ANN} (GPa)	Error (%)
RAC*	13.9	17.5	30.46	119.14	18.39	5.09
RAC**	13.9	22.8	30.46	119.14	18.39	19.34

****RAC at 28 days; *Calculated from Equation 1; *Calculated from Equation 2**

IV. CONCLUSION

The following conclusions can be derived from this study:

- 1) RCAs are a viable option for structural concrete in The Gambia.
- 2) The compressive strength and elastic modulus of RAC can be higher than that of NAC with varying water-to-cement ratios and coarse aggregate replacement percentages.
- 3) The compressive strength and elastic modulus of RAC can be predicted using ANN models, as they were acceptable and performed better than the established correlation equations from the BS code.
- 4) Concretes made with a replacement ratio greater than 50% require lower water/cement ratios (about 6–21%) and higher cement consumption (about 5–20%) than concretes made with 100% natural aggregate.
- 5) Results of the ANN model proposed in this work showed a reduction of 8% in elastic modulus for concretes made with 100% recycled aggregate when the WCR increased 25%. On the other hand, when analyzing concrete produced only with natural aggregate, an increase of 25% in the WCR generated a 15% reduction on the concrete elastic modulus.
- 6) ANNs can be used within the civil engineering field to solve further problems. They could also easily be used to model mechanical properties of concrete made with RAs derived from different sources (recycled brick aggregates, recycled mortar aggregates, etc.).

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CONFLICT OF INTEREST

The authors declare that there is no conflict of interest before, during and after carrying out the research work.

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