APPLICATION OF ARTIFICIAL INTELLIGENCE FOR PREDICTING THE COMPRESSIVE STRENGTH OF CONCRETE USING NATURAL AGGREGATE

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ABSTRACT

This seminar presentation explored the application of various artificial intelligence techniques such as Artificial Neural network (ANN), Adaptive Neuro-Fuzzy Inference System (ANFIS) and Multiple Linear Regression (MLR) for predicting the compressive strength of concrete using natural aggregates. Twenty-seven different experimental data points which was augmented to 180 data points was used in the study. The ANN, ANFIS and MLR models were developed, trained, tested and validated with the augmented data using MATLAB software. Statistical evaluators like the R^2, MSE and the RMSE was used to evaluate the algorithm with the strongest predictive capability. The results obtained from the analysis revealed distinct performance variations among the three AI models studied. Both the ANN and ANFIS models consistently demonstrated superior predictive capabilities compared to the MLR model. The ANN gave R^2 of 1, MSE of $8.66e^{-26}$ and RMSE $2.94e^{-13}$, the ANFIS gave R^2 values of 1, MSE of 0.00033 and RMSE of 0.0183 while the MLR reported R^2 values of 0.1243, MSE of 85.93 and RMSE of 9.27. The ANN model was adjudged to be the best prediction model for concrete containing natural aggregate based on the performance metrics.

Keywords: Adaptive Neuro-Fuzzy Inference System ANFIS, Artificial Neural Network ANN, Bida Natural Gravel BNG, Compressive Strength, Multiple Linear Regression MLR

Introduction

Concrete, a widely used construction material, has been favoured for centuries due to its affordability, widespread availability, long-lasting durability, and resilience in extreme weather conditions. In terms of production, concrete surpasses steel by tenfold in terms of tonnage (Zongjin, 2011). Its exceptional compressive strength, considered a key indicator of concrete quality (Neville, 2005), makes it a preferred choice in construction projects worldwide. Concrete stands out as the most versatile and extensively employed construction material globally. Unlike natural stone or steel, which are generally used as-is, concrete can be tailored to meet a wide range of performance requirements. To compensate for its lower tensile strength, concrete is typically reinforced with steel bars, resulting in what is known as reinforced concrete (Mehta and Monteiro, 1993; Shetty, 2005; Neville, 2011). The composition of concrete involves a combination of cement, supplementary cementing materials, aggregates, water, and chemical admixtures, which are proportioned appropriately and allowed to set and harden over time.

The properties of concrete heavily rely on the quality of its constituent materials. Among these properties, high compressive strength after 28 days of casting is particularly crucial. Therefore, evaluating the compressive strength of concrete is essential for assessing its quality and determining its suitability for construction purposes.

Aggregates play a vital role in concrete, accounting for 75% or more of its total volume and significantly influencing its overall characteristics. Therefore, the properties of aggregates are crucial in ensuring high-quality concrete. It is essential that aggregates possess strength, durability, and are free from contaminants such as silts, organic matter, oils, and sugars. Additionally, aggregates should exhibit hardness and robustness. Several key attributes define high-quality aggregates, including resistance to abrasion, freeze/thaw cycles, and sulfates. They should also have appropriate shape, surface texture, a well-graded composition, optimal density, and desirable compressive and flexural strength. Aggregates can be sourced from materials like sand, crushed rock, recycled concrete rubbles (Tantawi, 1988; Qasrawi *et al*., 2012; Mehta and Monteiro, 2014), or other sources. They can be classified as natural or artificial, with natural aggregates obtained from quarries or riverbeds, while artificial aggregates are derived from industrial by-products like blast furnace slag (Abebe, 2005; Neville, 2011).

One substitute aggregate of particular interest in this project is Bida Natural Gravel (BNG), which has been studied as an environmentally friendly alternative to crushed granite as coarse aggregate in concrete. BNG not only reduces environmental and ecological impacts but also exhibits excellent flowability and comparatively high compressive strength when used in concrete. BNG is a by-product of the Precambrian decomposition, transportation, and deposition of rocks in the Bida basin, located in the North Central part of Nigeria. Geographically, it is bounded to the North-East and South-West by the basement complex (Nuhu, 2009; Alhaji, 2016; Yusuf *et al*., 2021).

The Artificial Neural Network (ANN) is a computational model inspired by the functioning of biological nervous systems, such as the human brain. ANNs have the ability to learn and generalize from input data, even when it contains errors or is incomplete. Similar to how humans learn through examples, ANNs are powerful tools for solving complex engineering problems. The processing elements in a neural network resemble neurons in the brain and consist of simple computational elements organized in layers. (Fischer and Igel, 2014, Muhammet*et al*., 2012). They typically include an input layer, one or more hidden layers, and an output layer.

One effective estimation technique for complex problems is the Adaptive Neuro-Fuzzy Inference System (ANFIS). ANFIS combines the capabilities of fuzzy logic and neural networks and offers the learning ability of ANNs to establish and utilize correlations betweeninput and output elements. Supervised learning is employed in ANFIS, which consists of a learning algorithm, multilayer feedforward networks that incorporate input/output variables, and fuzzy rules (Loan *et al*., 2018).

Multiple linear regression is a statistical method used to model the relationship between a dependent variable and multiple independent (explanatory) variables. It is employed when there are multiple variables that potentially contribute to explaining or predicting the response variable. In a multiple linear regression analysis, all relevant variables are incorporated into the model. Models fitted to data in this statistical process are referred to as regression models (Leona et al., 2012; Gregoire, 2014; Gulden *et al*., 2013).

Significance of the Study

The prediction of compressive strength in concrete is a complex task due to the intricate nature of its components and proportions, as well as the sensitivity of concrete characteristics to its fresh state properties. Therefore, employing artificial intelligence becomes necessary as they offer efficient, fast, and accurate ways to predict concrete properties. Accurate prediction of compressive strength can result in significant time and cost savings, reduced material wastage, and provide a general indication of concrete quality, as compressive strength is often correlated with other concrete properties. Existing methods have limitations in considering the simultaneous effects of numerous parameters on compressive strength prediction, resulting in discrepancies between predicted and actual strength values.

Artificial intelligence such as Artificial Neural Network (ANN), Adaptive Neuro-Fuzzy Inference System (ANFIS), and Multiple Linear Regression (MLR) have been widely used in various civil engineering applications in recent decades (Shafahi, 2003; Vahdani, 2003) and have proven effective in data processing for laboratory work (Jang, 1993). However, there is limited literature on the application of ANN, ANFIS, and MLR for predicting the compressive strength of concrete incorporating Bida Natural Gravel (BNG). Hence, this research is justified as the developed models can serve both research purposes and practical applications in the field.

Considering the ongoing depletion of natural resources and the resulting ecological imbalance, there is a need to explore alternative aggregates that can help mitigate this issue. BNG, which has been reported to be eight times cheaper than crushed granite (Alhaji, 2016), presents itself as a potential solution. Additionally, studies have shown that naturally occurring stones can be used in concrete as long as their engineering properties are known and satisfactory. Therefore, investigating the use of artificial intelligence to predict the compressive strength of concrete incorporating BNG is well-justified.

Materials and Method

Materials

The materials utilized in this study include water, Ordinary Portland cement, fine river sand (as fine aggregates), and Bida Natural Gravel (as coarse aggregates). These materials underwent testing and were compared against relevant standards and specifications to ensure their suitability for concrete production.

Water

Water serves two primary purposes in concrete: it is essential for thoroughly blending the concrete mixture to achieve the intended workability, and it plays a crucial role in the cement hydration process. Consequently, for the concrete mixing and curing processes, potable water sourced from the tap at the Civil Engineering Laboratory of the Federal University of Technology, Minna, was utilized. This approach aligns with the guidelines outlined in BS EN 1008 (2002).

Ordinary portland cement (OPC)

CEM 1, as per the categorization outlined in NIS 87:2004, was the commercially available Ordinary Portland cement (OPC) used in producing all concrete specimens in this study. The cement was sourced from local retailers in the Minna town area and underwent testing in compliance with the requirements specified in BS EN 197-1 (2000).

Fine river sand

Fine river sand, collected within the Minna area, was obtained and prepared specifically for the production of concrete required in this study.

Bida natural gravel (BNG)

Bida Natural Gravel (BNG) is a naturally occurring stone with a brownish-red color, located in Bida, Niger State, Nigeria. It is found abundantly in the middle of the Niger Basin in Nigeria, with deposits spanning several metric tons (Salihu, 2011; Nuhu, 2009). The BNG used in this study was collected, washed, and subsequently sun-dried for further processing.

Methods

Specific gravity (SG)

The specific gravity (SG) of a material is defined as the ratio of the mass of a sample of that material to the mass of the same volume of water. In this study, specific gravity tests was conducted on both the fine aggregate and coarse aggregates, following the procedures and specifications outlined in BS EN 12620 (2008). The specific gravity was calculated using the expression given in Equation 3.1, which is provided by the standard. The specific gravity test allows for the determination of the density of the aggregates relative to the density of water.

$$\text{Specific gravity} = \frac{W2 - W1}{W} \quad (3.1)$$

W = (W4 - W1) – (W3 - W2) = weight of water displaced by sample

Let the Weight of density bottle = W1

Weight of density bottle + sample = W2

Weight of density bottle + sample + water = W3

Weight of density bottle + water = W4

Bulk Density Test

The bulk density test is a significant parameter that determines the volume of fine aggregates and cement paste required to fill the voids created by coarse aggregate grains. It provides information about the mass of material occupying a unit volume. In this study, both loose and compacted bulk density tests were conducted on both the fine and coarse aggregates, adhering to the specifications outlined in the relevant code or standard.

Weight of sample divider = W1

Weight of sample divider + sample = W2

Weight of sample = W2−W1 = W

$$\text{Bulk density} = \frac{W}{V} \quad (3.2)$$

The specimen divider was weighed while empty and recorded as W1. It was then filled using a scoop, the surface was then leveled with a straight edge. The specimen divider filled with the aggregates was weighed and the bulk density was then computed using Equation 3.2.

The volume (V) of the specimen divider = L x B x H (3.3)

Where:-

L = Length of specimen divider

B= Breadth of specimen divider

H = Height of specimen divider

Aggregate Impact Value (AIV) Test

The Aggregate Impact Value (AIV) is a measure of the resistance of a material to the effect of an unexpected shock or impact. In this study, the AIV test was conducted specifically on the coarse aggregates (BNG), following the procedures and specifications outlined in BS 812-112 (1990).

The AIV test was performed on aggregates that pass through a 14.0 mm sieve but are retained on a 10.0 mm sieve. It is important to note that the Aggregate Impact Test is not conducted on aggregates with sizes larger than 14 mm.

The AIV was calculated using the following expression:

$$AIV = \frac{M2}{M1} * 100 \quad (3.4)$$

Where

M1 = mass of the BNG test sample (g);

M2 = mass of the BNG passing the 2.36 mm test sieve (g).

Model development for ANN

In this study, the MATLAB (2015) software from MathWorks was employed to develop the model utilizing various Artificial Neural Network (ANN) architectures. The aim was to determine the most suitable architecture for the task at hand. The developed ANN was trained to recognize and interpret inputs, generating corresponding outputs based on the input data. The process of developing the ANN architecture involved several steps. These steps included selecting the number of layers, which consisted of the input layer, one or more hidden layers, and the output layer. Additionally, the number of neurons in each layer was determined, the appropriate activation function was chosen, weights and biases were assigned, and a training algorithm was selected. In this particular study, five input parameters were utilized: Water/cement ratio (w/c), weight of water (Ww), weight of cement (Wc), weight of fine aggregate (Wfa), and weight of BNG (WBNG). The output of the model focused solely on the Compressive Strength. The network underwent multiple training, retraining, and simulation iterations until the smallest error between the actual experimental data and the model output was achieved. The performance of the trained model was evaluated using metrics such as Mean Square Error (MSE), Root Mean Square Error (RMSE), and Regression (R).The specific architecture employed in this study consisted of a single hidden layer comprising 80 neurons. The Train LM training function was chosen, as it facilitated effective learning and optimization during the training process. The Log sig activation function was used for the hidden layer, while the Purel in activation function was employed for the output layer. Table3.1 shows the parameters utilized in the ANN models.

Table 3.1 - Input parameters for the ANN models

Parameter	Configurations
Input data	$w/c, W_w, W_c, Wf_a, W_{BNG}$
Output data	Compressive strength
Maximum number of epochs	4
Performance goal	2.78e-24
Learning rate	0.001
Momentum constant	0.1
Training function	TrainLM
Activation function	Hidden layer – Logsig and Tansig; Output Layer- Purelin
ANN architectures tried	5:80:1

Development of ANFIS

The development of the adaptive neuro fuzzy inference system (ANFIS) model for predicting the compressive strength of concrete with BNG as coarse aggregates involved the following steps:

(i) Preparation of Datasets: The datasets generated by MINITAB for the ANN models were used in this step to prepare the datasets for the ANFIS model.

(ii) Training the Model: The training dataset was utilized to train the ANFIS model using the ANFIS-based subtractive clustering algorithm. As there are multiple input neurons, this algorithm was employed to effectively train the model.

(iii) Validation of the Model: The testing dataset, which is a percentage of the total dataset used in the training process, was used to validate the ANFIS model. Several error criteria such as Root Mean Square Error (RMSE) and R-squared (R^2) were employed for model validation.

To analyze and defuzzify the implemented data, a fuzzy algorithm was utilized to classify the data and assign values representing the degree of truth or membership function. The membership function (MF) captures the degree of truth in the classification, and its type and shape are determined based on the data type and related uncertainties. Triangular or trapezoidal-shaped MFs are suitable for data with accelerated dynamic variation, while Gaussian types are used for analytical data requiring high accuracy. The bell-shaped MF is commonly employed for data related to construction and construction materials (Vakhshouri and Nejadi, 2014).

Identifying the most influential input parameters on the output involved developing and training ANFIS models based on each individual input parameter. The precision of training the ANFIS model focusing on a single input parameter indicates its potential as a sole predictor of the output. The impact of each input parameter on the output can then be evaluated using statistical error indices such as Root Mean Squared Error (RMSE) and Coefficient of Determination (R^2).

Multiple linear regressions (MLR)

Regression modeling is a statistical tool used for examining and understanding the relationships between variables by fitting models to data. It allows us to observe the interactions between variables and make predictions based on these relationships. Regression modeling can be categorized into two types: linear regression and multiple regression.

Linear regression focuses on the relationship between a single independent variable and its corresponding output variable. However, in many real-world problems, including the one addressed in this study, there are multiple independent variables that influence the output. In such cases, multiple regression is employed.

Multiple regression models are created by identifying the line or equation that minimizes the sum of the squared vertical distances between the data points and the line. This approach allows for the analysis of how multiple independent variables collectively affect the dependent variable (Deepa et al., 2010; Jacek *et al*., 2017; Norzima *et al*., 2012).

The general form of a multiple linear regression model can be represented by the equation:

$$Y = a0 + \sum_{j=1}^{m} ajXj \qquad (3.5)$$

In the above model, Y is the model's output, Xj, 's are input variables to the model while a0 , a1 ..... am are partial regression coefficients or parameters. The parameters are calibrated and trained in such a way that the model's output becomes similar to experimental output on the training data set. For the purpose of this work, one optimization model was employed to minimize an error function like mean square error (MSE) and other error functions.

Results and Discussion

Results

The sieve analysis of fine aggregate and coarse aggregate (BNG) was obtained through laboratory work. The obtained results are in accordance with BS 882 and are as shown in figure 4.1 and 4.2. Compressive strength of concrete obtained ranges between 13.12 – 44.3N/mm^{2}as shown in table 4.1 while a summary of physical properties of constituent materials are shown in table 4.2.

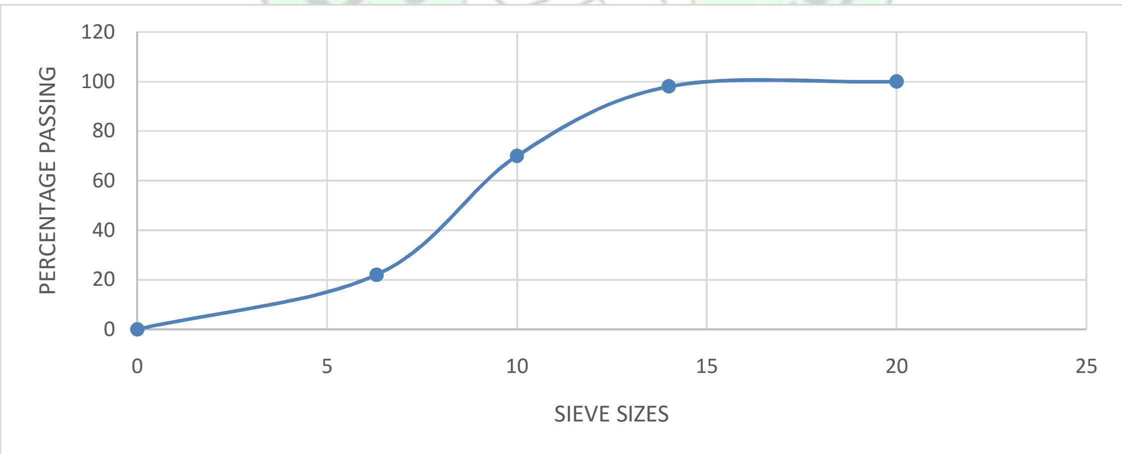

Figure 4.1: Sieve Analysis result for Bida natural stone

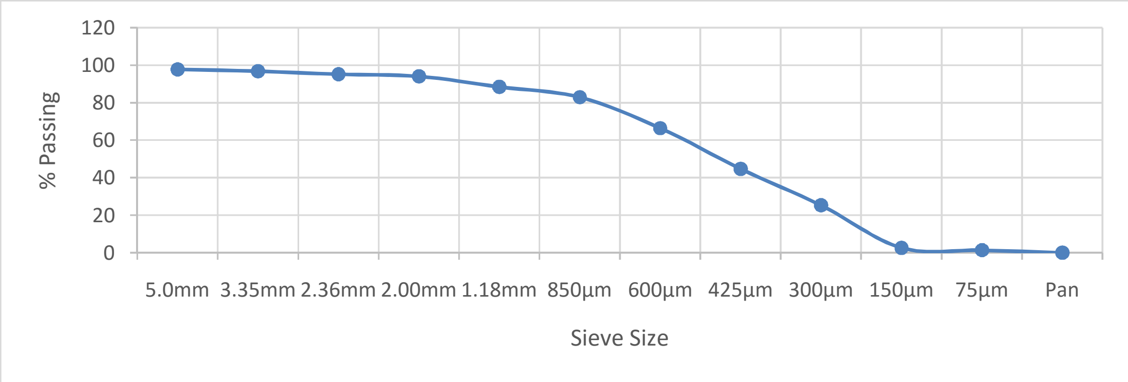

Figure 4.2: Sieve Analysis result for fine aggregate

Table 4.1: Compressive Strength

Parameters	Range
Compressive strength	13.12 – 44.3N/mm^2

Table 4.2: Summary of Physical properties of constituent materials

Parameters	Sand	Bida Natural Gravel	Typical Range
Specific Gravity	2.62	2.61	2.5 - 3
Compacted Bulk density(kg/m^3)	1610.79kg/m^3	6.48	1200 - 1950
Uncompacted Bulk density(kg/m^3)	1389.21 kg/m^3	8.66	1200 - 1950
Aggregate Impact Value (AIV)		19.87	≤ 30

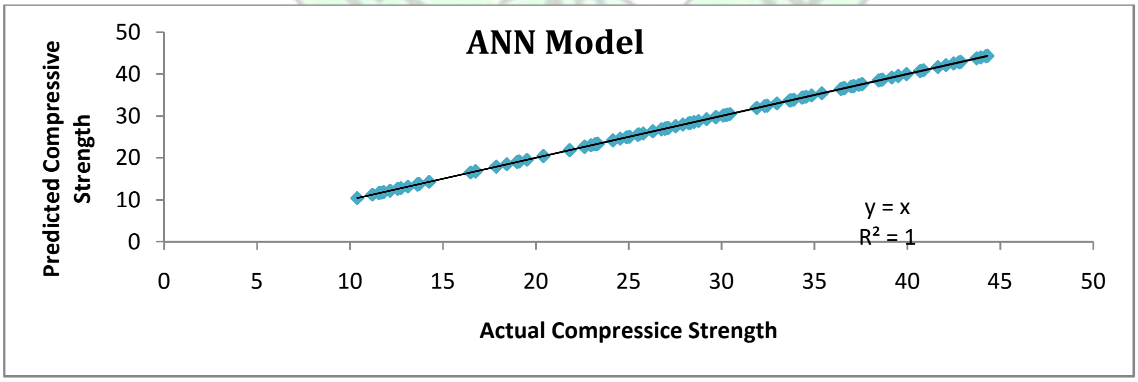

Figure 4.3: Regression Chart for the chosen ANN model result

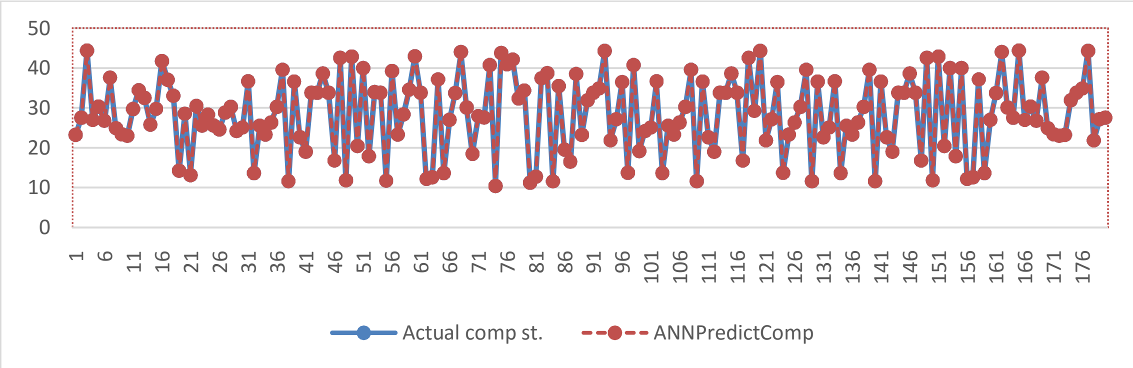

Figure 4.4: The Actual and Predicted trend-line for the ANN model

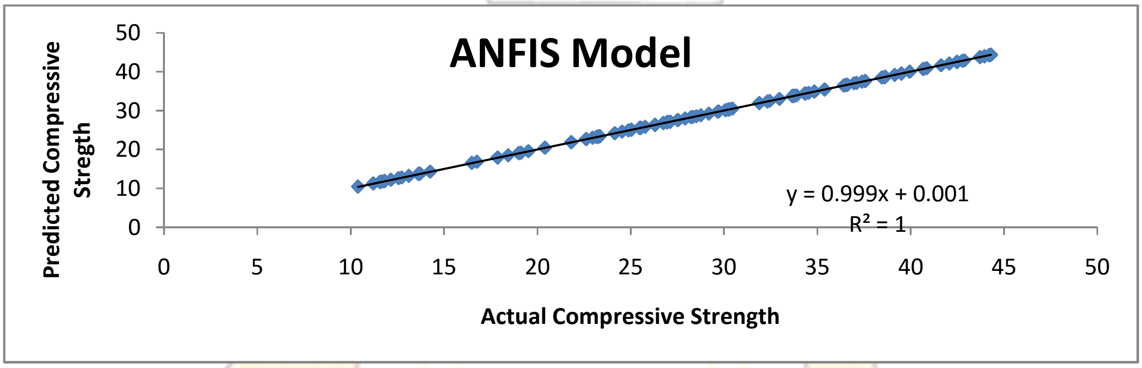

Figure 4.5: Regression chart for the ANFIS model result

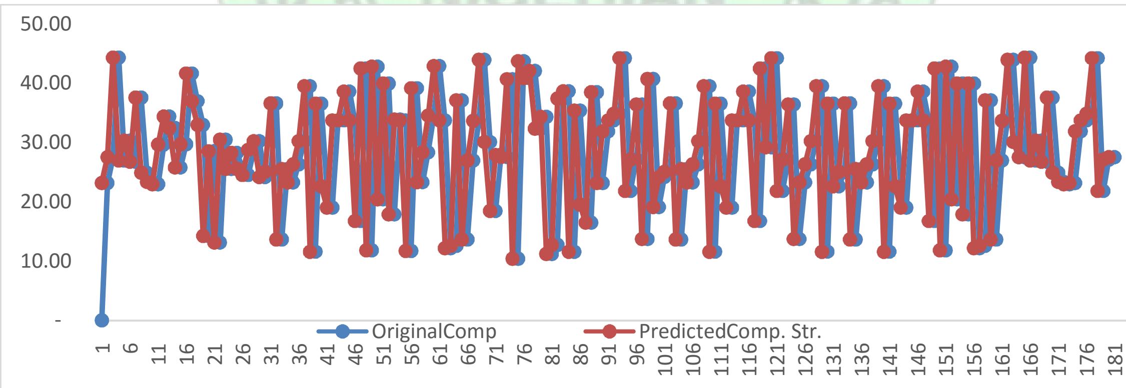

Figure 4.6: The Actual and Predicted trend-line for the ANFIS model

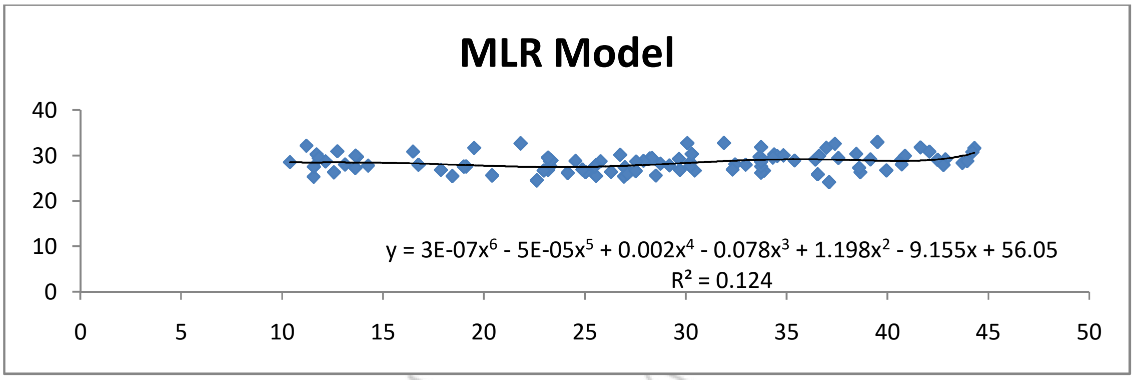

Figure 4.7: Regression chart for the MLR model result

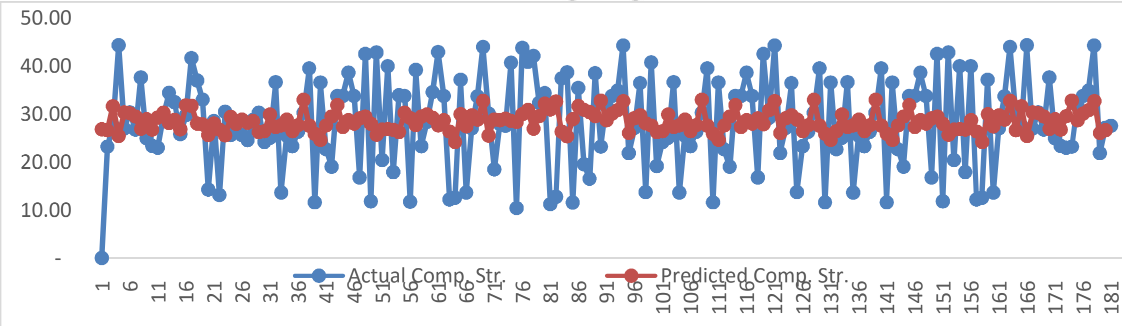

Figure 4.8: The Actual and Predicted trend-line for the MLR model

Table 4.3: The statistical evaluation for all the Compressive Strength models

Statistical Evaluators/ Models	ANN	ANFIS	MLR
R^2	100%	100%	12.43%
RMSE	$2.94e^{-13}$	0.0183	9.27
MSE	$8.66e^{-26}$	0.00033	85.93

Discussion of results

In comparing the performance of different algorithms, it was observed that both the ANN as shown in figure 4.3 and 4.4 and ANFIS models as shown in Figure 4.5 and 4.6 outperformed the MLR model indicated in figure 4.7 and 4.8 in predicting the compressive strength. As shown in table 4.3, the ANN models achieved high R-squared (R^2) values and low Root Mean Square Error (RMSE) values of 100% and $2.94e^{-13}$ respectively, indicating a robust predictive performance. Similarly, the ANFIS model demonstrated a strong predictive capability with perfect R^2 values of 100% and significantly low RMSE values of 0.0183. On the other hand, the MLR model exhibited a very low

R^2 value and high MSE and RMSE values, indicating its inability to accurately capture the complex relationships within the data.
These findings differ from the research conducted by Majeed et al. (2021) and Dao *et al.* (2019), who concluded in their separate studies that ANFIS models consistently outperformed other algorithms, including ANN and MLR models, in predicting concrete properties such as compressive strength. It is worth noting that the ANN model may have performed even better if multiple trials were conducted to select the most accurate one, as done in this study. However, Yusuf (2021) affirmed that the ANN model is a powerful tool for modeling the compressive strength of concrete made using BNG. Overall, the results suggest that both the ANN and ANFIS models are highly suitable algorithms for accurately predicting the compressive strength in concrete applications. These models provide valuable insights for optimizing concrete mix designs and ensuring structural integrity.

Figure 4.9 illustrates the comparison between the actual experimental compressive strength data and the predicted values obtained from the ANN, ANFIS, and MLR models using both training and testing data. The predicted values of both the ANN and ANFIS models align closely with the actual data, indicating their strong agreement. However, the MLR model exhibits a limited range of trend values. The trend-line algorithms of the ANN and ANFIS models show a perfect alignment with the actual values, as depicted in Figure 4.9. These results are further supported by examining the coefficient of determination (R^2) values for each model. The findings have significant implications for accurately predicting compressive strength in concrete applications, with both the ANN and ANFIS models demonstrating superior predictive capabilities among the evaluated models.

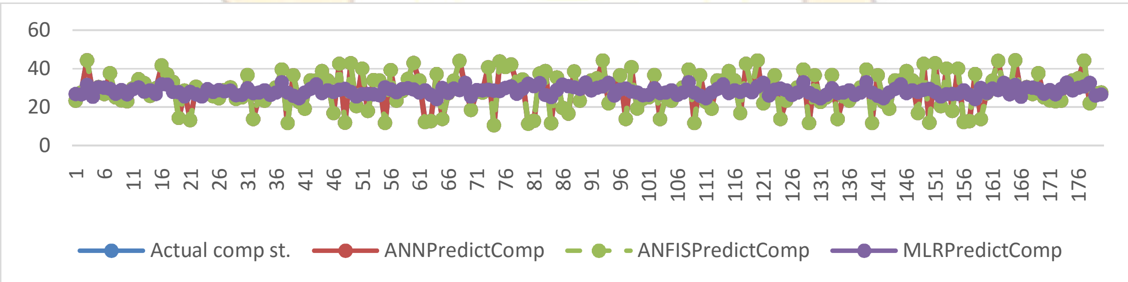

Figure 4.9: Actual and the Predicted values for the ANN, ANFIS and MLR model

Conclusion
In conclusion, this study has examined the physical and mechanical properties of the constituent materials utilized. These properties align with the standard specifications for aggregates in concrete. The compressive strength of concrete incorporating Bida Natural Gravel (BNG) ranged from 13.12 to 44.3 N/mm^2.

The analysis results demonstrated notable variations in performance among the three AI models investigated. The Artificial Neural Network (ANN) and Adaptive Neuro-Fuzzy Inference System (ANFIS) models consistently exhibited superior predictive capabilities compared to the Multiple Linear Regression (MLR) model. The ANN model produced an R^2 value of 1, an MSE of 8.66e^{-26}, and an RMSE of $2.94e^{-13}$. Similarly, the ANFIS model yielded an R^2 value of 1, an MSE of 0.00033, and an RMSE of 0.0183. In contrast, the MLR model showed an R^2 value of 0.1243, an MSE of 85.93, and an RMSE of 9.27. Based on the performance metrics, the ANN model was deemed the most effective prediction model for concrete incorporating BNG.

Recommendations

The research findings and conclusions provide the basis for the following recommendations:

1. Based on the physical and mechanical properties obtained for Bida Natural Gravel (BNG), it is recommended for utilization in the production of normal weight concrete. The properties meet the necessary criteria for concrete construction.
2. Researchers and concrete practitioners are encouraged to utilize the Artificial Neural Network (ANN) model, which demonstrated superior predictive capabilities in this study. The ANN model can be relied upon for accurate predictions of concrete properties and can enhance the efficiency of concrete-related research and practical applications.
3. It is suggested to conduct comparative studies involving additional AI algorithms such as Support Vector Machines (SVM), Random Forests, and Deep Learning. These studies will enable the assessment of their performance in predicting concrete properties and identify the most suitable techniques for accurate predictions. Exploring alternative AI algorithms can contribute to further advancements in concrete research and application.

REFERENCES

Abebe, D. (2005). The Need for Standardization of Aggregates for Concrete Production in Ethiopian Construction Industry. Unpublished Research submitted to Civil Engineering Department, Addis Ababa University, Ethiopia.

Alhaji, B. (2016). Statistical Modelling of Mechanical Properties of Concrete Made from Natural Coarse Aggregates from Bida Environs. Unpublished PhD Thesis, Department of Civil Engineering, Federal University of Technology, Minna.

BS 812 - 112 (1990). *Testing Aggregates. Method for Determination of Aggregate Impact Value.* British Standards Institution, London

BS EN 197- 1 (2000). *Cement- Composition, Specifications and Conformity Criteria for Common Cements*. British Standard Institution, London

BS EN 1008 (2002). *Mixing Water for Concrete. Specification, for Sampling, Testing and Assessing the Suitability of Water, including Water Recovered from Processes in Concrete Industry as Mixing Water for Concrete*. British Standards Institution, London.

BS EN 12620 (2008). *Aggregates for Concrete.* British Standards Institution, London.

Dao, D., Trinh, S. H., Ly, H. B., & Pham, B. T. (2019). Prediction of Compressive Strength of Geopolymer Concrete using entirely Steel Slag Aggregates. *Novel Hybrid Artificial Intelligence Approaches*, *Appl. Sci. 9*(11), 1113.

Deepa, C., SathiyaKumari, K., & Sudha, V. P. (2010). Prediction of the compressive strength of high-performance concrete mix using tree based modelling. *International Journal of Computer Applications*, Vol.6, No.5, pp.18-24.

Duch, W. (2005). Uncertainty of data, fuzzy membership functions, and multilayer perceptrons. *IEEE Transactions on Neural Networks, 16*(1), 10–23.

Fischer, A., &Igel, C. (2014). Training restricted Boltzmann machines: An introduction. *Pattern Recognition, 47*(1), 25-39.

Grégoire, G. (2014). Multiple Linear Regression. *EAS Publications Series, 66*, 45-72. doi:10.1051/EAS/1466005.

Gülden, K., Uyanik, N., &Güler (2013). A Study on Multiple Linear Regression Analysis. *Procedia - Social and Behavioral Sciences, 106*, 234-240. doi:10.1016/J.SBSPRO.2013.12.027.

Jacek, W., Pedro, J., & Rodriguez, E. (2017). Basics of Regression Models. In *Advances in Intelligent Systems and Computing* (Vol. 641, pp. 1-6). Springer. doi:10.1007/978-3-319-71156-0_1.

Jang, J. S. R. (1993). ANFIS: Adaptive-Network-based Fuzzy Inference Systems. *IEEE Transactions on Systems, Man, and Cybernetics, 23*, 665-685.

Joelianto, E., &Rahmat, B. (2008). Adaptive Neuro-Fuzzy Inference System with Error Back Propagation Algorithm using Mapping Function. *International Journal of Artificial Intelligence, 1*(A08), ISSN 0974-0635.

Leona, S. A., Stephen, G., Steven, C., Amanda, N., & Ingrid, C. (2012). Multiple Linear Regression Vol. 2. https://doi.org/10.1002/9781118133880.hop202018.

Majeed, M., Khalid, M., & Hameed, M. (2021). Prediction of Compressive Strength of High-Performance Concrete Using Multiple Linear Regression and Artificial Neural Networks Coupled with Cross Validation Technique. *Journal of Materials in Civil Engineering, 33*(2), 04020500. doi:10.1061/(ASCE)MT.1943-5533.0003626.

MATLAB. (2015). *Statistics Toolbox*. MathWorks, Inc., Natick, Massachusetts, United States.

Mehta, P.K. & Monteiro, P.J.M. (1993). *Concrete,* McGraw-Hill, Pennsylvania, New York.

Mehta, P.K., & Monteiro, P.J.M. (2014). Concrete: Microstructure, properties and materials (4th ed.). McGraw-Hill Education.

Minitab, Inc. (2017). *Minitab 17 Statistical Software*. Computer Software. State College, PA: Minitab, Inc. Retrieved from www.minitab.com.

Monika, K. (2021). Fuzzy membership function design: An Adaptive Neuro-Fuzzy Inference System (ANFIS) based approach. In *International Conference on Computer Communication and Informatics India*.

Muhammet, U., Ayça, A., Vedat, T., & Hasan, E. (2012). Artificial Neural Networks. In *Advances in Natural Computation* (pp. 5-17). doi:10.1007/978-3-642-32900-5_2.

Neville, A.M. (2005). Properties of Concrete. Pearson Longman, New York, USA.

Neville, A.M. (2011). Properties of Concrete. Pearson Longman, New York, USA.

Ngo, L. T. Q., Wang, Y.-R., & Chen, Y.-M. (2018). Applying Adaptive Neural Fuzzy Inference System to Improve Concrete Strength Estimation in Ultrasonic Pulse Velocity Tests. *Advances in Civil Engineering, 2018*, 1-11.

NIS 87 - Nigerian Industrial Standard (2004). *Standard for Sandcrete Blocks*. Standard Organization of Nigeria, Lagos, Nigeria.

Norzima, Z., Shahryar, S., & Alireza, A. (2012). Modeling for Regressing Variables. *Social Science Research Network*.

Noureen, T., Mohd, N., Mohd, S., & Kashif, H. (2017). An investigation of membership functions on performance of ANFIS for solving classification problems. In *International Research and Innovation Summit* (pp. 226). doi:10.1088/1757-899x/226/1/012103.

Nuhu, G. O. (2009). *Geology and Mineral Resources of Nigeria*. Springer Dordrecht Heidelberg, London.

Qasrawi, H., Marie, I., & Tantawi, H. (2012). Use of recycled concrete rubbles as coarse aggregate in concrete. In *Proceedings of the 5th Jordanian International Civil Engineering Conference*, Amman, Jordan.

Salihu, A. T. (2011). A Study of the Compressive Strength of Concrete Made from Bida Natural Deposit Stone. Unpublished M.Eng Thesis, Department of Civil Engineering, Federal University of Technology, Minna.

Shafahi, Y. (2003). Trip Generation Modeling Using Neural Network System. *Journal of Faculty of Engineering, University of Tehran, 36*(3), 361-370.

Shetty, M.S. (2005). *Concrete Technology*. S.Chand& Company Ltd., India.

Srikanta, M., & Akhil, D. (2017). Regression Modeling and Analysis. In *Practical Guide to Regression Analysis* (pp. 69-96). doi:10.1016/B978-0-12-803279-4.00004-3.

Tantawi, H. M. (1988). Employing Science and Technology to produce low cost concrete housing. In *Symposium on Simplification and Dissemination of Science and Technology in Rural Areas*, Mu'tah, Jordan.

Vahdani, S. (2003). Analysis of Resonance Effect in V-shaped Alluvial Valley Using Adaptive Network-Based Fuzzy Inference System, *Journal of Faculty of Engineering, University of Tehran,* 37(1), 63-74.

Vakhshouri, B., &Nejadi, S. (2014). Application of adaptive neuro-fuzzy inference system in high-strength concrete. *International Journal of Computer Applications, 101*(5), 39–48.

Yusuf, A. (2021). Application of Neural Network for predicting properties of Concrete using Bida Natural Gravel as Coarse Aggregates. Unpublished PhD Thesis, Department of Civil Engineering, Federal University of Technology, Minna.

Zongjin, Li (2011). Advanced Concrete Technology. John Wiley & Sons, Inc., Hoboken, New Jersey