Nnamdi Azikiwe University Journal of Civil Engineering (NAUJCVE)

Volume-6, Issue-2, pp-29-35
www.naujcve.com

Research Paper Open Access

Compressive Strength Prediction in GGBS-Based Concrete using Regression Model Equation

***Ifie-emi Francis Oseke, [1]Deinmodei Maxwell and [2]Elsie Bogofanyo Mondigha**

* Department of Civil Engineering, Federal University Otuoke

[1] Department of Civil Engineering, National Water Resources Institute

[2]Nigerian Building and Road Research Institute

Corresponding Author: **engroseke@gmail.com**

ABSTRACT *: Concrete exposed to a conventional environment exhibits some levels of predictability under serviceability, while highly uncertain in the deterioration behavior of concrete is when concrete is in marine environment. Based on a laboratory based data-driven approach, this study considered the possibility of developing a regression model equation to predict the compressive strength over long curing age and provide an excellent opportunity to understand the complexity of concrete strength development dynamics in real practice. The 7-days measured early compressive strength value and the absolute density respectively were modeled as the input parameters. The 28-days strength value were predicted and compared with a laboratory measured actual 28-days strength values. The resulting two-parameter interaction based on regression model analysis is given as* $Y_{28th\ day\ Strength}$ *= -55.1664 + 0.2146*(7-day strength) + 0.0387*(absolute density). The validation findings using Multiple R = 0.92,* R^2 *= 0.85, Adjusted* R^2 *= 0.55 and the Standard Error = 0.83, shows that both the 7-day strength and absolute density have a positive effect in predicting* 28^{th} *day strength as the dependent variable. Specifically, a one-unit increase in 7-day strength improves the predicted value of the dependent variable by 0.2146 units, while a one-unit increase in absolute density increases it by 0.0387 units, while holding other factors constant. Thus, the application of regression model equation in the prediction of compressive strength is effective and the results can be employed in the design satisfactorily and the model can be employed in the assurance of quality control in construction sites*

Keywords: *Compressive Strength, Regression Model, Prediction and Concrete*

Date of Submission: 23-10-2026 Date of acceptance: 07-11-2026

I.INTRODUCTION

The strength of concrete remains the fundamental characteristics utilized for quality assurance during construction, as designing a concrete structure requires the concrete compressive strength to be used. Characteristic strength of the concrete is designated as the compressive strength of a concrete sample that has been cured for up to 28 days and is determined by the standard cylinder crushing test. However, due to environmental exposure, there are rising issues that alter the strength credentials of the hardened concrete, which includes environments where concrete is exposed to and consist of: Ions, chloride, magnesium, calcium, and potassium amongst other chemical components. Together, these components initiate chemical reaction and in some cases dissolved carbon dioxide affect the strength of concrete.

According to Oseke et al., (2017), the performance of concrete directly affects structural safety, durability, and service life, with compressive strength serving as the key indicator of load-bearing capacity. In practice, compressive strength is typically measured through standardized laboratory tests. However, these tests require curing periods of up to 28 days, limiting their usefulness for decision-making in construction, especially when exposed to seawater environment.

Seawater is fairly uniform in chemical composition, which is characterized by the presence of about 3.5% soluble salts by weight. The ionic concentrations of Na+ and Cl are the highest, typically 11,000 and 20,000 mg/liter, respectively (Nwofor and Sule 2012). However, from the standpoint of aggressive action to cement hydration products, sufficient amounts of $Mg2^+$ and SO_2 are present typically 1400 and 2700 mg/liter respectively. The pH of seawater varies between 7.5 and 8.4, the average value in equilibrium with the atmospheric CO_2 being 8.2. Under exceptional conditions (i.e., in sheltered bays and estuaries) pH values lower than 7.5 may be encountered (Onwuka et al., 2011). These are usually due to a higher concentration of dissolved CO_2 which would make the seawater more aggressive concrete thereby affecting its strength development.

To address this limitation, models have been developed as a data-driven approach for predicting the complex relationships between concrete composition and mechanical performance. In this context, a recent study published in MDPI Materials, “Performance Comparison of Machine Learning Models for Concrete Compressive Strength Prediction” evaluates different machine learning models for estimating concrete strength and compares their predictive performance.

Models act a dependable, accurate, and scientific mathematical approach to assess concrete mix test data and other experimental results thereby lowering the likelihood of

failures occurrence without full-scale testing. Through correlation analysis, statistical performance indices can also shed light on the major variables affecting compressive strength of concrete. Consequently, a significant number of studies have been conducted in the active field of concrete compressive strength prediction research, with many attempting to develop a suitable mathematic model which is capable of predicting strength of concrete at various ages with acceptable high accuracy.

In this regard, developed in this study is an effort to establish a connection between the strength of concrete and its components and to articulate this connection using mathematical model. The models were designed with a friendly user interface for easy application by practitioners and professionals. The concrete strength can be ascertained without the specified waiting for the 28 days curing by using models. As a result, engineers and project managers might be better equipped to plan construction activities.

II. MATERIALS AND METHODS

2.1 Materials

Water, cement, fine and coarse aggregates, and mineral pozzolans of Ground Granulated Blast-furnace Slag (GGBS) will all be used in this study. Lafarge cement based in the United Kingdom provided the GGBS while the Portland cement was sourced from the local market here in Nigeria. The physical property of specific gravity of the cement, and GGBS was found to be 3.12, and 2.85 respectively.

The fine aggregates that make up river sand were categorized in zone 2 with a specific gravity of 2.67, whereas the coarse aggregate employed in this study was well graded with a normal size of 10–20 mm and a specific gravity of 2.60. The chemical composition of the Portland cement and the GGBS is presented in Table 1

Table 1: Chemical Composition of Cement and Ground Granulated Blast-furnace Slag

Oxide	CaO	SiO_2	Al_2O_3	MgO	Fe_2O_3	MnO	SO_3
Cement	63.000	20.000	6.000	4.210	3.000	0.030-1.110	2.0
(GGBS)	41.990	35.350	11.590	8.040	0.350	0.450	0.230

2.2 Methods

2.2.1 Experiment Design

Mix design of the ground granulated blast-furnace slag (GGBSbased concrete was based on guidelines laid out in BS EN 12390-3:2009 which involved the selection and proportioning the different replacement levels of the GGBS. The mix design for the control M11 (Concrete without GGBS) was obtained via trial mixes, and the replacement levels at 10%, 20% and 30% of GGBS, as shown in Table 2. The experimental design mix was selected having met the requirement for the design strength of grade 40 concrete.

Table 2: Mix Proportions for Different Specimens

Mix Code	Material Composition	Cement (Kg/m^3)	Coarse Aggregates: (kg/m^3)		Sand (kg/m^3)	Water (kg/m^3)	GGBS (kg/m^3)
			20/10	10/4			
MI1	Aggregates+Sand+Cement	420	210	230	880	189	0
MI2	Aggregates+Sand+Cement+10%GGBS	378	210	230	880	189	42
MI3	Aggregates+Sand+Cement+20%GGBS	336	210	230	880	189	84
MI4	Aggregates+Sand+Cement+30%GGBS	294	210	230	880	189	126

2.2.2 Mathematical Model for GGBS-Portland Cement based Concrete

The development of a mathematical model to predict concrete strength has been the focus of recent study. The following is a description of the standard regression equation used to simulate concrete's compressive strength is shown in equation 1.

$$f = b_o + b_1 . \frac{w}{c} \quad (1)$$

Where:

f = Compressive strength of concrete

b_o, b_1 = Empirical coefficients

$\frac{w}{c}$ = Water/Cement ratio

The application of this idea in Equation 1 relies on a linear regression model aimed at predicting the compressive strength of standard concrete, which builds upon Equation 2 that was initially formulated by Abram (1919) and given as follows Equation 2:

$$f = \frac{A}{B^{\frac{w}{c}}} \quad (2)$$

Where:

f = Compressive strength of concrete; A and B are empirical coefficients

$\frac{w}{c}$ = Water-cement ratio

A, B = empirical constants

It is common knowledge that the compressive strength of concrete decreases linearly as the water-cement (w/c) increases, hence the strength of concrete increases linearly with cement-water ratio (c/w), which modifies the Equation 2 to 3.

$$f = A + B . \frac{w}{c} \quad (2)$$

$$f = \frac{A}{B^{\frac{w}{c}}} \quad (3)$$

Where:

f = Compressive strength of concrete

$\frac{w}{c}$ = Cement / water ratio

A, B = empirical constants

The model does not take into consideration the amounts of cement, fine aggregate and coarse aggregate when predicting the strength of concrete. As such, the strength of different concrete mixes will be the same if their w/c ratio is constant, which is untrue. Therefore, efforts should be concentrated on models, taking into account the influence of mix constituents on the concrete strength in order to have more reliable and accurate results for the prediction of concrete strength. In this regard, modification is made to include other variables in the form of linear regression equation into Equation 3 and used widely to predict the compressive strength of various types of concrete as given in Equation 4

$$f = b_0 + b_1 \frac{w}{c} + b_2 \text{ CA} + b_3 \text{ FA} + \text{C} \quad (4)$$

Where:

f: compressive strength of concrete

$\frac{w}{c}$: water/cement ratio

C: quantity of cement in the mix

CA: quantity of coarse aggregate in the mix

FA: quantity of fine aggregate in the mix

Again, based on Equation 4, all variables connected to compressive strength are linearly related; however, this is not always the case, as the factors involved in a concrete mix that influence its compressive strength are interconnected, and their additive effect is not consistently applicable. This indicates the necessity for an alternative mathematical model that can accurately predict concrete strength with a high degree of reliability. Therefore, if we consider the general structure of multiple linear regressions is given as shown in Equation 5.

$$Y = a_0 + a_1 X_1 + a_2 X_2 + a_3 X_3 + \ldots\ldots\ldots a_m X_m \quad (5)$$

According to Steven et al., (1989), for cases involving curvilinear (non-linear) multiple dependency, the application of a logarithmic transformation is appropriate in transforming the regression analysis using Equation 6.

$$log_{(y)} = log_{(a_0)} + a_1 log\,(X_1) + a_2 log\,(X_2) + a_3 log\,(X_3) + \ldots\ldots\ldots a_m log\,(X_m) \quad (6)$$

Equation 6 can further be transformed back into a format that anticipates the dependent variable (Y) by utilizing the antilogarithm to generate an equation of the type as shown in Equation 7

$$Y = a_0 X_2^{a_1} \cdot X_2^{a_2} \cdot X_2^{a_3} \ldots\ldots\ldots\ldots\ldots\ldots X_m^{a_m} \quad (7)$$

The equation 7, otherwise called referred to as the multivariable power equation demonstrates that in engineering contexts, variables are typically dependent upon numerous independent variables which is found to be suitable for prediction of concrete strength's development of concrete.

III. RESULTS AND DISCUSSION

3.1 Effect of Ground Granulated Blast-furnace Slag on Concrete Strength Development

The effects of different replacement levels of Portland cement with GGBS on the compressive strength for all the c different various mixes is shown in Figure 1. The control mix without Portland cement alone was reported as (MI1), while mixes M12 with 10%, M13 with 20% and M14 with 30% replacement levels were the mixtures prepared with the GGBS up to the 14 and 28 days curing strength. The strength increases as the percentage of GGBS increases. The higher compressive strength shown by the concrete containing GGBS can also be attributed to the better PC-to-GGBS interlock (interfacial bonding). Compressive strength depends mainly on the type of cement in the mortar paste and the type of aggregates; the cement/aggregate (fine and Coarse) bond (Oseke, and Dangiwa, 2025). A good understanding of concrete's compressive strength can assist in the appropriate selection of material to minimize or possibly maximize the heat of hydration, which is influenced by the proportion of the tricalcium silicate (C_3S) in the cement that causes an increase in the rate of heat of evolution at early ages of the hardened concrete

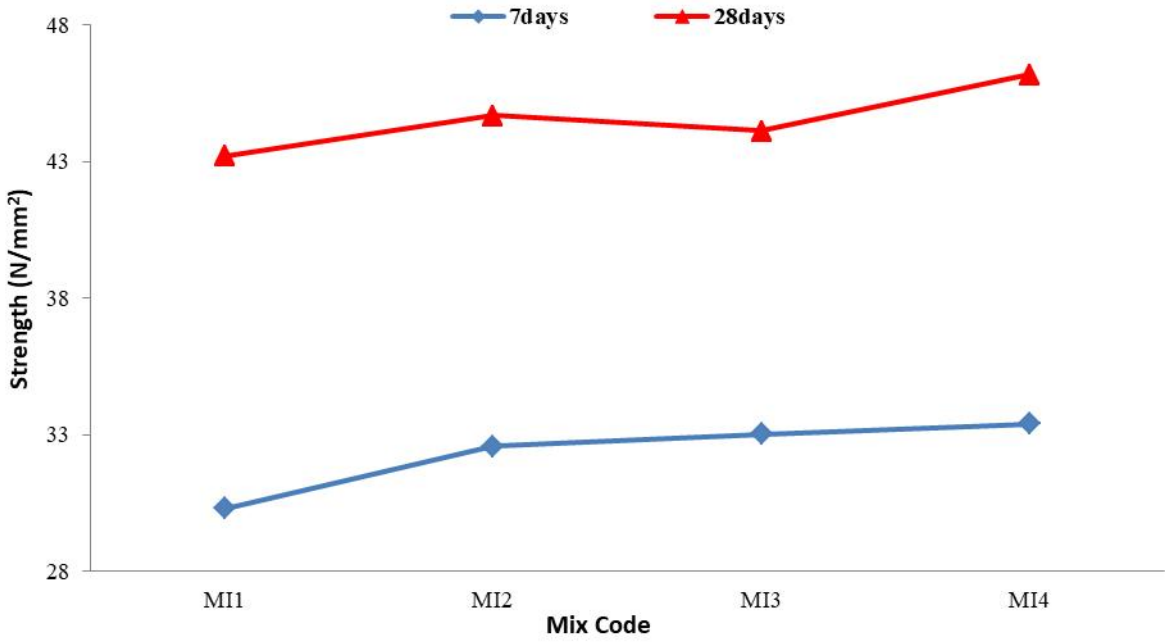


Fig.1: 7 Days curing compressive strength compressive strength results for specimens

3.2 The Absolute Density of the GGBS- Concrete

The variables provided from the experimental work aside the early 7 days curing strength for the proposed model is the

absolute density rather than the bulk density. The absolute density table of the control concrete (MI1) with regards to the GGBS replacement mixes (MI2 – MI4) after 7 days curing is shown in Figure 2The results revealed that the densities for all the concretes casted were within the acceptable limit for hardened concrete density ranging from (2373 to 2426 kg/m^3), Since the same weight of material was used for all mixes, although with different percentage level of GGBS replacement, but the strength varied because of the differences in the reaction mechanism of the GGBS used in the mixing process. According to Ezeh and Ibearugbulem, (2009), while bulk density is essential for mix design, batching, and determining the overall compaction and volume of voids, absolute density is more closely linked to the intrinsic structural and compressive strength of the solid concrete matrix.

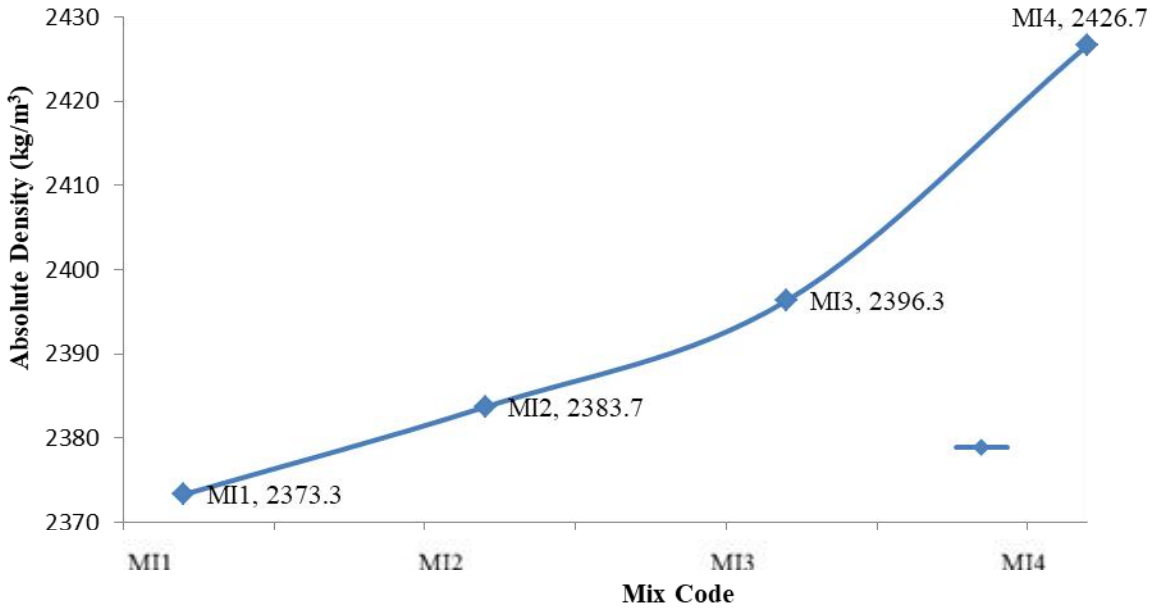


Fig.2: The 7 Days curing density of concrete cube specimen

3.3 Regression Model Equation for GGBS- Concrete

The regression model parameters for the prediction equation with the analyzed coefficients is presented in Table 3, while the 28 days predicted strength compared with the actual strength plotted on the doubled axis model output depicting the near perfect correlation is shown in Figure 3. The relationship is strengthened by the residual coefficient (actual – predicted) between the actual and predicted strength outcome. According to Mama, and Osadebe, (2011), the residual coefficient is helpful because it calculates the deviation between a model's prediction and reality, which aids in error diagnosis and increases predictive accuracy

Table 3: Regression model prediction parameters

Parameters		Coefficient	
Intercept		b_0	-55.1664
7 Days Compressive Strength	X_1	b_1	0.2146
Absolute Density	X_2	b_3	0.0387

Based on the regression model analysis, the 28-day strength prediction model for this ready mix plant dataset is given in Equations 8.

$$Y_{28^{th}\ \text{day Strenght}} = -55.1664 + 0.2146 * (\text{7-day strength}) + 0.0387 * (\text{Absolute Density}) \quad (8)$$

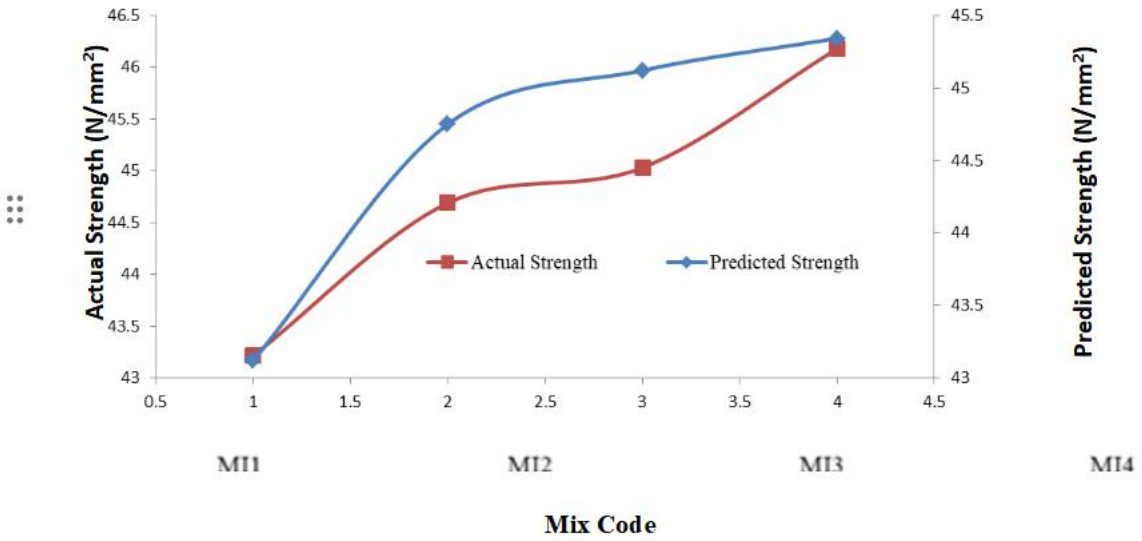


Fig.3: Model accuracy; actual vs predicted 28 day strength

3.4 Regression Model Validation

The summary statistics based on the regression equation using the using 7-Day Strength to predict 28-Day Strength is presented in Table 4. Typically, the multiple R is the correlation coefficient between the actual values and the predicted values from the regression model. The result shows multiple R value close to 1, indicating a very strong positive linear relationship (Oseke et al., 2021).

The adjusted R^2 which is a modified version of R^2 has been adjusted for the number of predictors in the model. The adjusted R^2 increases only if the new term improves the model more than would be expected by chance (Moriasi et al., 2005). It decreases when a predictor improves the model by less than expected by chance. It is always lower than the R^2. The model with the highest adjusted R^2 and only statistically significant independent variables. The result demonstrated that, 85% (R^2 = 0.85) of variation from the actual dataset is explain by the prediction model.

The Adjusted R^2, which modifies the R^2 by accounting for the number of predictors in the model, penalizes the addition of unnecessary variables (. The result indicates that 55% of the original dataset is explained after internal adjustment for model complexity was made during the regression analysis.

The standard error typically measures the average distance that the observed values fall from the regression line and it's essentially the standard deviation of the residual. The results indicated that the model only recorded an average prediction error of about 0.83 units. According to Liebe (2002), smaller standard error values indicate more accurate predictions.

Table 4: Summary output from regression equation

	Regression Statistics
Multiple R	0.92
R^2	0.85
Adjusted R^2	0.55
Standard Error	0.83

IV. CONCLUSION

In order to forecast the concrete's compressive strength based on the early age test results, a basic mathematical model is presented in this study, using a regression-based mathematical equation to predict the concrete strength development as it ages over a period of time. In this regard, the early strength results with various replacement levels of GGBS for Portland cement are employed to obtain credible strength prediction values. A simple and practical approach for predicting the 28-day compressive strength of concrete using the early 7-day strength and the absolute density is investigated in this study, and the proposed technique can be utilized as a dependable instrument for analyzing the strength of concrete from very early results.

REFERENCES

[1]. Oseke, (2017): Concrete incorporating ground granulated blast -furnace slag, *Nigerian Journal of Scientific Research* 16 (3)

[2]. Nwofor, T.C., and Sule, S. (2012): Stability of Groundnut Shell Ash (CSA)/Ordinary Portland Cement (OPC) Concrete in Nigeria, *Pelajia Research Library*, **3**(4): 2283-2287

[3]. Onwuka, D. O., Okere, C. E., Arimanwa, J. I. and Onwuka, S. U, (2011): Prediction of concrete mix ratios using modified regression theory, *Computational Method in Civil Engineering*. Vol. 2, (1), pp 95 – 107.

[4]. Abrams L.D., ((1919): Properties of Concrete. *Pitman Publishing Limited,* London.

[5]. Oseke, I. F. and Dangiwa, F. P. (2025): Optimal cement replacement levels in concrete using ground granulated blast furnace-slag for workability and strength development. *Open Journal of Engineering Science*, Volume: 6; Issue: 1, Pages: 01 –14 (2025)

[6]. Ezeh, J. C. and Ibearugbulem, O. M. (2009): Application of Scheffe's Model in Optimization of Compressive cube Strength of River Stone Aggregate Concrete". *International Journal of Natural and Applied Science*, 5(4), pp 303 – 308.

[7]. Mama, B. O. and Osadebe, N. N. (2011): Comparative analysis of two mathematical models for prediction of compressive strength of sandcrete blocks using alluvial deposit". *Nigerian Journal of Technology,* Vol. 30 No 3, pp. 82 – 89.