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Experimental and Statistical Evaluation of Mechanical Properties of Green Cement Concrete – Taguchi Integrated Supervised Learning Approach

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Abstract

Globally, rapid infrastructure development and environmental challenges associated with the higher carbon footprints of ordinary Portland cement (OPC) based concrete have increased the usage of green cement-based concrete (GCC) to reduce energy consumption and provide a sustainable option. Even though GCC is a superior alternative to OPC, only a few publications have addressed optimizing process parameters in GCC manufacturing to optimize mechanical properties. The Taguchi method is well-known as one of the most effective methods for optimizing predictors to get the desired level of response. Additionally, in the modern era, data-driven supervised machine learning approaches have been used extensively to develop mathematical models to establish relationships between the variables. As a result, the Taguchi method was used in this study to obtain the best mix design targeting a compressive strength of greater than 40 MPa. Numerous design combinations have been tested, and a process for selecting the most effective combination has been established. The analysis aided in comprehending the individual contributions of the major components to the mechanism of strength gain. The observations confirmed the Taguchi method's ability to predict the design mix proportions of the GCC and the ability of machine learning to relate the variables mathematically.

Keywords: Alkali activation; Green cement; Concrete; Construction; Machine learning.

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1. Introduction

Concrete buildings and other structures are constructed in most of the world's countries. The concrete industry's contribution to the development of contemporary society and economy and its contribution to environmental deterioration are undeniable.[1,2] Improving the sustainability of concrete structures is a challenge for the entire concrete industry. The World Business Council for Sustainable Development defines sustainable development as forms of progress that meet the needs of the present without jeopardizing future generations' ability to meet their own needs.[3] Traditionally, only the compressive strength of concrete is used to assess its quality; it is assumed that making concrete "stronger" makes it better in all ways. However, as it becomes clear that this assumption is flawed, attention shifts away from a sole reliance on compressive strength and toward considerations of the usefulness (in the broadest sense of the term) of a specific concrete.[4-9] Green cement (GC), also known as alkali-activated cement (AAC) and geopolymer, a techno-economic alternative,[10] has shown the potential of transforming solid aluminosilicate minerals into green cement, with less carbon dioxide (CO_2) emissions and lower energy requirements than ordinary Portland cement (OPC).[11] When compared to OPC-based concrete mixes, AAC-based concrete exhibits comparatively better performance when exposed to elevated temperatures.[11] The alkali-activation technology involves making inorganic cement to repurpose wastes or industrial by-products from various commercial activities.[12,13] The use of alkali-activated materials as binders in concrete production has attracted growing attention due to the cement and concrete industry's demand for emissions reduction, energy

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conservation, and environmental concerns.[14] Additionally, the hardening rate of AAC is faster than that of OPC due to the presence of a high calcium content because of the use of recycled aggregates derived from building and demolition wastes.[12]

The use of alkali-activated concrete is an ideal option for sustainable concrete. It allows for the substitution of natural resource components, reduction of CO_2 emissions, and significant improvement of mechanical qualities.[15] The mechanical properties of alkali-activated concrete are strongly influenced by several variables, including the type of alkali activator used, the alkali-silica reaction, the alkali concentration, the slag content, and the aggregate content.[16-18] The influencing variables, particularly the sodium silicate solution, when used for the alkali activation, must be used carefully as indicated by the life cycle assessment of various mix designs concerning AAC. The alkali-silicate reaction (ASR) occurs in concrete when the alkali pore fluids in the concrete react with the silicious aggregate particles. ASR products exhibit a strong affinity for moisture. When the pressure exceeds the concrete's tensile strength, cracks form, allowing additional water permeation through migration and gel swelling. Consider the reaction to proceed according to the idealized equations represented by Equations 1 and 2. However, the ASR cannot proceed in a concrete specimen if the alkali concentration is less than a certain threshold value.[19–22]

$$4SiO_2 + 2NaOH \rightarrow Na_2Si_4O_9 + H_2O \quad (1)$$

$$3SiO_2 + 2NaOH \rightarrow Na_2Si_3O_7 + H_2O \quad (2)$$

Nevertheless, the life cycle assessment comparison for OPC and AAC concrete indicated that the AAC-based concrete had better mechanical properties and lesser environmental impact for a similar proportion.[23] Thus, the investigation of various possible mix designs obtained from the above-mentioned parameter combinations to fabricate the AAC becomes a crucial element of research and a hot topic for scholars and practitioners.[24] Even though AAC-based concrete is widely recognized as one of the most effective technologies in the concrete industry, there have been few studies on its evaluation, particularly concerning the optimization of parameters.[25]

For example, Thomas and Peethambaran[26] examined the compressive strength of green cement concrete concerning specimen size and curing conditions. Bondar *et al.*[14] devised a method for determining the proportions of constituents in green cement concretes (GCC) based on their packing fraction. Thomas *et al*.[26] also presented the results of an experimental study on chloride permeability in alkali-activated fly ash, alkali-activated slag, and Portland cement concrete and suggested that there were differences in chloride binding potential between GCC and OPC through salt ponding tests. Kovtun[27] researched the influence of preconditioning on the durability indices of GCC and concluded that if specimens were forcefully preconditioned at elevated temperatures, durability testing could produce misleading results on GCC's durability performance. Mehta *et al*.[28] used the Taguchi method to optimize several parameters, including the ratio of alkali solution to fly ash, sodium silicate to sodium hydroxide, fine aggregates to total aggregates, sodium hydroxide concentration, total aggregate content, and curing temperatures, for the development of fly ash-based GCC. The response factors chosen were compressive strength, sorptivity, chloride permeability, and microstructural characteristics of the resulting GCC. Ibrahim *et al*.[29] evaluated the performance of GCC in the presence of acid while improving the reaction parameters using an artificial neural network (ANN), a machine learning algorithm, in conjunction with the response surface method (RSM). Binder systems are critical in developing GCCs' qualities, from strength to long-term durability. As a result, Wang *et al*.[30] optimized the GCC using binder system features. Gomaa *et al*.[31] used supervised rain forest regression modeling, a machine learning technique, to forecast the qualities of fresh and hardened GCCs and to optimize their physiochemical properties and process parameters. According to the reviewed literature, the GCC is extremely sensitive to changes in the chemical compositions and quantities of the elements affecting the mechanical properties.

Additionally, there is a hurdle in determining the optimal ratio and combination of all elements to prepare GCC. Only a few publications have been published to date, focusing on the mixed design of components based on the target mean strength, as it takes many trials to determine the effect of each ingredient on the properties of fresh and hardened GCC. As a result, there is a need to develop a method for GCC mix design that can save time, effort, resources, and energy. In the current experimental study, the Taguchi method is used to determine the optimal constituent proportions for the GCC's specific mix design with a design target compressive strength of greater than 40 MPa, and a supervised machine learning approach is used to create the mathematical model. The input parameters have been chosen in accordance with the degree of GCCs effect on the target characteristics in the fresh and hardened states determined during the pilot study. Fig 1 illustrates the presented work completely in a pictographic manner.

2. Materials and methods

2.1 Materials

The nearby steel plant supplied blast furnace slag with a specific gravity of 2.85. Table 1 lists the chemical components of slag. The alkaline activator utilized in this work was a mixture of sodium hydroxide and sodium silicate with a SiO_2/Na_2O ratio of 2.6:1. To prepare the needed concentration of sodium hydroxide, 98 percent pure sodium hydroxide was

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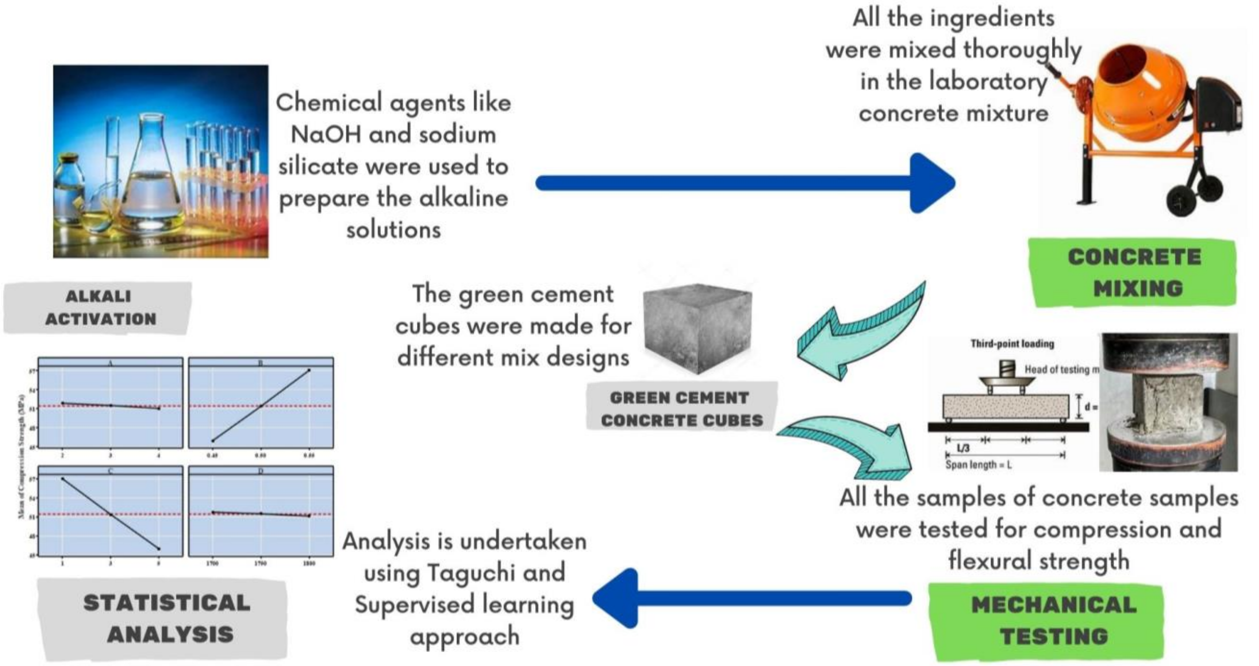

Fig. 1 Schematic representation of the adopted methodology.

Table 1. Chemical compositions of GCC.

Elements	Na_2O	K_2O	SO_3	MgO	Fe_2O_3	Al_2O_3	SiO_2	CaO
Mass%	0.4	0.85	2.36	8.45	0.52	6.32	36.5	35.2

dissolved in water. Crushed sand with a fineness modulus of 3.24, a saturated surface dry specific gravity of 2.94, water absorption of 0.78%, and a maximum size of 4.95 mm were used as fine aggregates. As for coarse aggregates, crushed stone with a nominal maximum size of 10 mm, a saturated surface dry specific gravity of 2.58, and water absorption of 0.6% was employed. The blended aggregates were chosen to meet the specimen criteria specified by ASTM C33 Standard Specification for Concrete Aggregates.[32]

2.2 Specimen preparation

The 50 × 50 × 50 mm cubic specimens for compressive tests and 40 × 40 × 160 mm prismatic specimens for the flexural tests were made for the experimental study. The mixing was carried out at around 27 °C in a laboratory room. Initially, slag and aggregates were combined for approximately 5 minutes in their dry condition state. The alkaline activator was then added to the mixture and stirred for 5 minutes. A 55-liter motorized 'SUN LABTEK' concrete mixer Model: SL-CC-077 was used to mix the components. After pouring the mix into the cylindrical molds, they vibrated for one minute. After 24 hours, all specimens were de-molded and conditioned in a controlled environment of 50% relative humidity and 20°C before testing.

2.3 Experimental method

ASTM C39/C39M-21, Standard Test Method for Compressive Strength of Hydraulic Cement Mortars (Using 2-in. or 50-mm cube specimens), was used to determine the compressive strength.[33] According to ASTM standards, the rate of development in compressive strength of concrete is highest within the first 28 days after casting and then slows down. Additionally, concrete strength criteria are based on a 28-day age in most cases. As a result, the measurements were made after 28 days. A displacement-controlled universal testing machine (UTM) equipped with a 300-ton load cell was used. The loading velocity was set to 0.02 mm/s. Five specimens of each type were evaluated, and the average value was used as the compressive strength indicative of that specimen type. To assess the flexural strength of the prepared prismatic specimens, a three-point flexural test was conducted in accordance with the ASTM C78/C78M-21 Standard Test Method for Flexural Strength of Concrete. The test was conducted using a displacement-controlled UTM equipped with a 5-ton load cell. The loading rate was set to 0.002 mm/sec. Five specimens of each type were evaluated, and the mean value was used to determine the representative flexural strength for that specimen type. Fig. 2 illustrates the schematic representation of the mechanical tests conducted in the present study.

2.4 Experimental design

The Taguchi method is one of the most effective experimental methodologies for determining the minimum number of experimental runs required within the permissible factor and

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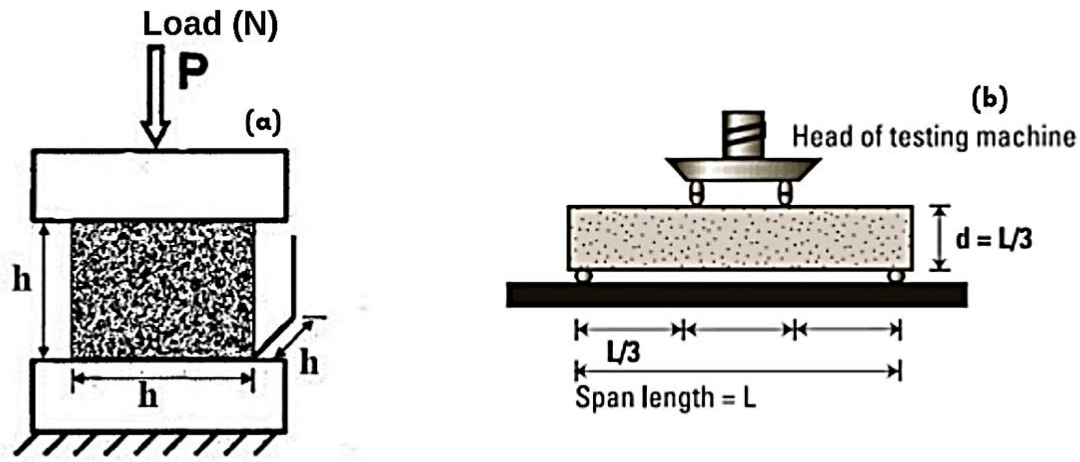

Fig. 2 Schematic representation of mechanical tests: (a) compressive strength test of a cubic concrete specimen; (b) three-point flexural test of the concrete specimen.

level limits by utilizing special orthogonal arrays to investigate all design factors.[34,35] The present study employs the Taguchi approach to choose the best green cement-based concrete to establish the best blend with the highest compressive and flexural strengths. The most significant factors are believed to be Factor A – sodium hydroxide (NaOH) solution concentration (in molar terms), Factor B – alkaline liquid to slag mass ratio, Factor C – sodium silicate (Na_2SiO_3) solution mass ratio, and Factor D – aggregate content. According to the pilot investigation, a NaOH content of between 2 and 4 molars offered adequate compressive strength values. Additionally, working with large doses of NaOH in the laboratory was not a safe or straightforward process. Additionally, alkaline liquid-to-slag ratios less than 0.4 did not give adequate workability. In contrast, values greater than 0.55 did not provide the required strength and were not economically viable, as the alkaline liquid is the most expensive constituent in the alkali-activated slag concrete mix. The same findings were obtained with a NaOH to sodium silicate ratio of less than one and greater than five. Additionally, the aggregate content was between 70% and 85%. The proposed design method in this study was based on a concrete density of approximately 2000 kg/m^3. Table 2 summarizes the components and their respective levels considered in this investigation.

Table 2. Factors and levels of each factor used in the Taguchi method.

Factor	Description	Level 1	Level 2	Level 3
A	Concentration of NaOH (M)	2	3	4
B	Alkaline liquid to slag ratio	0.45	0.50	0.55
C	NaOH to sodium silicate solution ratio	1	3	5
D	Aggregate content (kg/m^3)	1700	1750	1800

The present study used orthogonal arrays, OA_9 (3^4), which were created using the Taguchi method, as it is best suitable for cases having four design variables, each having three levels.[36] Table 3 and Table 4 detail the components of each mixture and the compositions of concrete mixtures. The water/solid mass ratio was kept constant at 0.4:1 for the trial mixtures to achieve the desired workability and strength. The water in the mixture was a combination of sodium silicate, sodium hydroxide, and additional water.

Table 3. The experimental variables of the mixture trials.

Trial No.	Concentration of NaOH (M) [A]	Alkaline liquid to slag ratio [B]	NaOH to sodium silicate solution ratio [C]	Aggregate content (kg/m^3) [D]
T1	2	0.45	1	1700
T2	2	0.50	3	1750
T3	2	0.55	5	1800
T4	3	0.45	3	1800
T5	3	0.50	5	1700
T6	3	0.55	1	1750
T7	4	0.45	5	1750
T8	4	0.50	1	1800
T9	4	0.55	3	1700

Table 4. Green cement-based concrete mixtures used for Taguchi optimization.

Mix	Slag (kg/m3)	NaOH solution (kg/m^3)	Sodium silicate (kg/m^3)	Aggregates (kg/m^3)	Added water (kg/m^3)
1	190.44	42.85	42.85	1700	70.66
2	171.30	64.25	21.40	1750	35.52
3	152.73	70.00	14.00	1800	15.40
4	160.00	54.00	18.00	1800	51.09
5	186.20	77.60	15.50	1700	40.04
6	167.27	46.00	46.00	1750	50.87
7	175.22	65.70	13.15	1750	58.04
8	156.40	39.10	39.10	1800	61.56
9	181.82	75.00	25.00	1700	45.25

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2.6 Supervised learning approach

The conventional laboratory-based method of determining mechanical properties can provide accurate and reliable estimates. However, this procedure requires skilled and equipped personnel to complete several time-consuming and complicated steps, including batch preparation, molding concrete samples, curing, and breaking the samples using expensive equipment. As a result, numerous attempts have been made in recent years to transition away from traditional laboratory-based methods and toward using empirical relationships to estimate mechanical properties. These methods provide cost-effective tools for rapidly estimating the mechanical properties of materials. Among these relationships, those developed using data-driven techniques have received considerable attention due to their capacity for learning from data and solving extremely nonlinear problems.[37] Machine learning is a branch of research that examines how to transform empirical data into useable models using computational algorithms. Machine learning algorithms can be used to (a) gain an understanding of the cyber phenomenon that generated the data under study, (b) abstract that understanding into a model, (c) forecast future values of a phenomenon using the model generated above, and (d) detect anomalous behavior demonstrated by a phenomenon under observation.[38] Supervised Learning is a critical subset of machine learning. It is dependent on the existence of a (potentially enormous) collection of multidimensional data referred to as a data set. Each piece in this collection is referred to as a data point. Each data point is contained within an invariant M-dimensional space called the feature space. Each constituent of a data point is referred to as a feature that may be continuous or discrete.[39] It is referred to as supervised learning because the learning process occurs while the observed label of observation variables is visible.[40] Linear regression is a supervised learning technique frequently used for forecasting, prediction, and relationship discovery in quantitative data.

It is one of the earliest forms of learning and is still widely used today.[41] It is the most basic, most popular, and most powerful method to determine the correlations between continuous predictor and response variables.[42] Linear regression is a useful tool used in a variety of studies. It determines the coefficients of a combination using independent observations and models a dependent variable Y in terms of a linear combination of p independent variables X = $[X_1]$, $[X_2]$...$[X_p]$.[43–45] Thus, in the present study, linear regression, a supervised machine learning approach, is used to present the mathematical model for predicting the compressive and flexural strength of the green cement-based concretes within the experimental limits for the given values of concentration of NaOH, alkaline liquid to slag ratio, NaOH to sodium silicate solution ratio and aggregate content.

3. Results and discussion

3.1 Results of Taguchi analysis of compressive and flexural strength

Table 5 details the Taguchi results for all the combinations. The main effect plots provide a general indication of the relative importance of the parameters in determining the system response. If the line for a given parameter in the main effect plots is near horizontal, the parameter has no considerable effect. A variable for which the line has the highest inclination, on the other hand, will have the most impact.[46] Figs. 3 and 4 show the main effects of means for compressive and flexural strength for green cement-based composites. The offered main effects graphs show the best

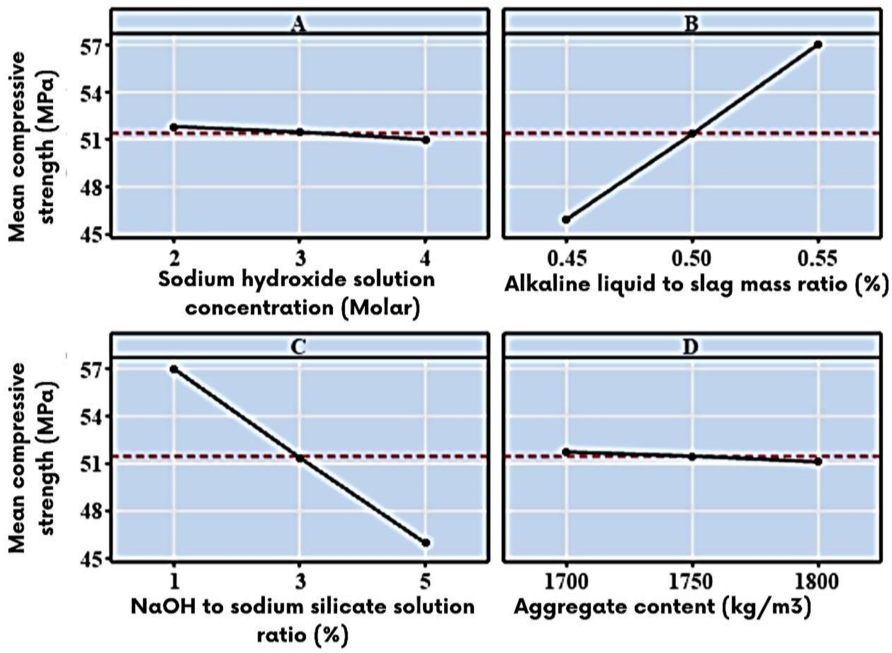

Fig. 3 Main effect plots of means for compressive strength versus selected input variables: A - Sodium hydroxide solution concentration; B - Alkaline liquid to slag mass ratio; C - NaOH to sodium silicate solution ratio and D - Aggregate content.

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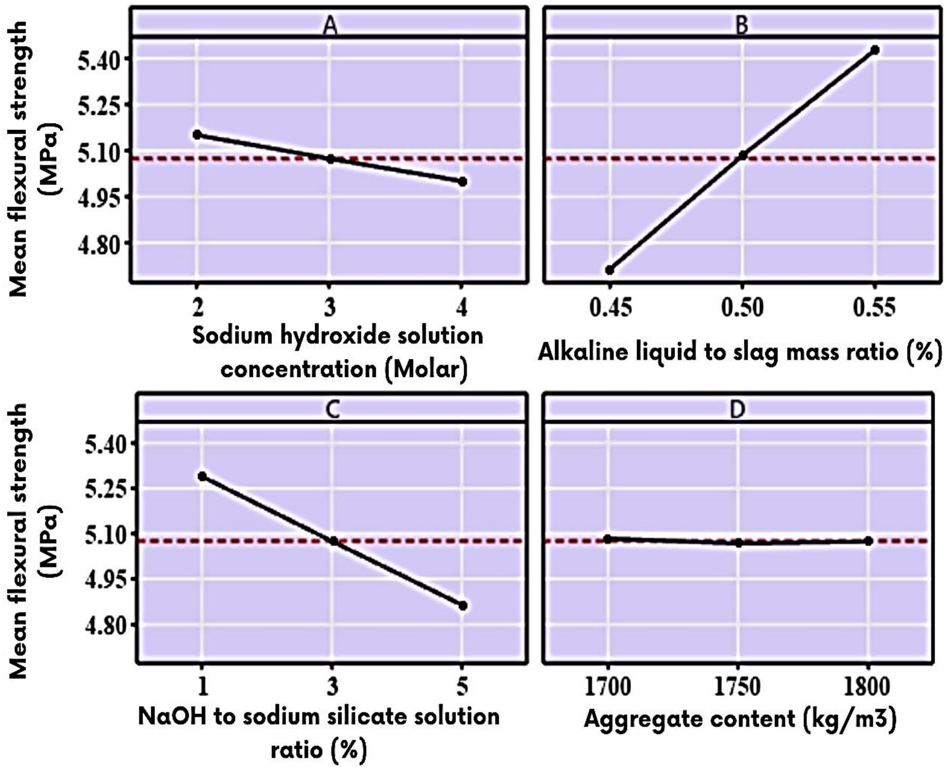

Fig. 4 Main effect plots of means for flexural strength versus selected input variables: A - Sodium hydroxide solution concentration; B - Alkaline liquid to slag mass ratio; C - NaOH to sodium silicate solution ratio and D - Aggregate content.

Table 5. The experimental variables of the mixture trials.

Trial No.	Concentration of NaOH (M) [A]	Alkaline liquid to slag ratio [B]	NaOH to sodium silicate solution ratio [C]	Aggregate content (kg/m^3) [D]	Compressive Strength (MPa)	Flexural Strength (MPa)
T1	2	0.45	1	1700	52.13	5.01
T2	2	0.50	3	1750	51.71	5.15
T3	2	0.55	5	1800	51.63	5.29
T4	3	0.45	3	1800	45.55	4.71
T5	3	0.50	5	1700	46.22	4.88
T6	3	0.55	1	1750	62.66	5.63
T7	4	0.45	5	1750	40.04	4.42
T8	4	0.50	1	1800	56.11	5.22
T9	4	0.55	3	1700	56.83	5.36

combination of predictive variables for the desired mechanical strengths. From the plots and the nature of the line, it can be inferred that considering the compressive strength, Factor A – sodium hydroxide solution concentration (in molar terms) and Factor D – aggregate content do not have a considerable effect, whereas Factor B – alkaline liquid to slag mass ratio and Factor C – NaOH to sodium silicate solution ratio has a significant effect on the compressive strength. In the case of flexural strength, the results are similar, except that there is also a slight effect of Factor A – sodium hydroxide solution concentration (in molar terms). Table 6 shows the best combination of parameters for the performance studies.

The environmentally friendly green cement-based composites exhibited an average compressive strength ranging between 40.04 MPa (T9) and 62.66 MPa (T6). Thus, all the fabricated GCC crossed the set target value of 40 MPa. According to the Taguchi analysis results, the T6 combination with a sodium hydroxide solution concentration of 3M, an alkaline liquid to slag mass ratio of 0.55:1, a NaOH to sodium silicate solution ratio of 1:1, and aggregate content of 1750 kg/m^3 is the best in terms of mechanical strength of green cement-based composites. The strengths increased with the increase in the value of the alkaline liquid to slag mass ratio. An increase in Na_2O% often enhances mechanical strength. This fact is evident from previous research.[47–49] This is because an increase in the alkali activator dosage results in a higher degree of reaction (showing the amount to which the slag particles are reacted).[50] From 2 M to 4 M, increasing the molar concentration of NaOH solution increases total sodium oxide (Na_2O).

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Table 6. ANOVA results for compressive strength of prepared GCC samples obtained from regression analysis.

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
Regression	4	369.165	99.98%	369.165	92.291	5357.56	0.000
A	1	1.033	0.28%	1.033	1.033	59.99	0.001
B	1	185.927	50.35%	185.927	185.927	10793.13	0.000
C	1	181.610	49.19%	181.610	181.610	10542.55	0.000
D	1	0.595	0.16%	0.595	0.595	34.56	0.004
Error	4	0.069	0.02%	0.069	0.017		
Total	8	369.234	100.00%				

Additionally, the increase in molar concentration also decreases the components of the alkaline solution (SiO_2/Na_2O, H_2O/Na_2O, and H_2O/SiO_2) in the combination. In general, increasing the concentration of NaOH solution facilitates the dissolution of complex aluminosilicate compounds during the early reaction stage due to more Na_2O. This results in the release of calcium oxide (CaO), silicon oxide (SiO_2), aluminum oxide (Al_2O_3), and aluminum silicate (Al_xSi_yO) monomers present in the concrete binders, thereby favoring strength development.[49] It is well established that the strength is highly dependent on the silicate concentration in the grout.[51] When an aqueous sodium silicate solution and an activating agent are used to manufacture green cement-based concrete, the silicate solution reacts to generate a colloid that polymerizes further to form a gel that improves strength, stiffness, and permeability primarily in granular soils.[52] Thus, as the silicate concentration falls due to an increase in the NaOH to sodium silicate ratio, the mechanical strength of the resulting GCC decreases. Scanning electron microscopy (SEM) and X-ray diffraction (XRD) microstructural studies can provide additional insight into the material and chemical composition changes that occur in the selected types of concrete samples. Nonetheless, it falls outside the scope of the present study and can be considered a future topic of research for researchers working on green cement-based composites.

3.2 Mathematical models for compressive and flexural strength using supervised learning

The Taguchi analysis results provide a clear picture of the effects of various parameters used in the present study. However, linear regression analysis, a supervised machine learning approach, is used to further develop mathematical models to (a) accurately estimate the effects of the predicting variables and (b) have a general mathematical model that brickmakers and researchers can use to estimate the compressive and flexural strength of their fabricated bricks for known values of the predicting variables used in this study. Tables 6 and 7 represent the analysis of variance (ANOVA) results obtained from the linear regression analysis for compressive and flexural strength, respectively.

All of the selected input variables have a significant effect on the mechanical strength of the generated GCC samples, according to the ANOVA results at the 95% confidence interval. However, the percentage impact of Factors A and D, which reflect the NaOH concentration and aggregate content, is less than 5% on the variance in the mechanical properties measured and can be ignored. The results of ANOVA obtained through the linear regression analysis adhere to the result obtained in the Taguchi analysis. Moreover, it is seen that Factor B – alkaline liquid to slag mass ratio is determined to have the maximum impact on the fabricated GCC samples and contributes 50.25% to the variance in compressive strength and 71.56% to the variance in flexural strength, followed by Factor C – NaOH to sodium silicate solution ratio, contributing 49.19% to the variance in compressive strength and 25.20% to the variance in the flexural strength. The linear regression equations for predicting the compressive and flexural strength are mathematically represented by Equations 3 and 4, respectively. Table 8 represents the summary of the linear regression analysis for the compressive and flexural strength tests.

$$Compression\ strength, CS\ (MPa) = 16.29 - 0.4150\,A + 111.33\,B - 2.7508\,C - 0.00630\,D \quad (3)$$

$$Flexural\ strength, FS\ (MPa) = 2.225 - 0.07500\,A + 7.133\,B - 0.10583\,C - 0.000100\,D \quad (4)$$

Figure 5 shows the residual graphs for compressive strength. Fig. 5(a) shows compressive strength data that is virtually straight, showing a strong correlation between experimental and projected values. The difference between experimental and anticipated compressive strength values in Fig. 5(b) is modest, ranging from –0.2 to 0.2 on the conventional residual scale. Figs. 5(c) and 5(d) show the residual variation frequency and the observed sequence of experiments and residuals. The figures show a propensity for running in both positive and negative directions, meaning that observed and anticipated values are highly correlated.

Figure 6 shows the residual graphs for flexural strength. Fig. 6(a) shows compressive strength data that is virtually straight, showing a strong correlation between experimental and projected values. The difference between experimental and anticipated flexural strength values in Fig. 6(b) is modest, ranging from –0.02 to 0.02 on the conventional residual scale. Figs. 6(c) and 6(d) show the residual variation frequency and the observed sequence of experiments and residuals. The figures show a propensity for running in both positive and negative directions, meaning that observed and anticipated values are highly correlated.

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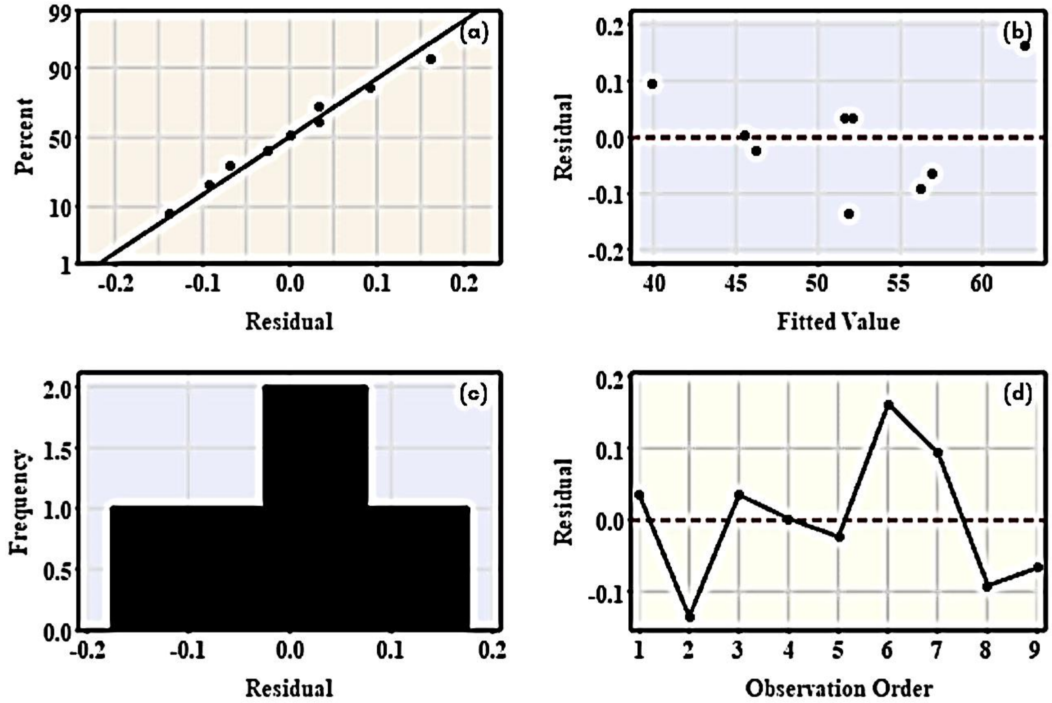

Fig. 5 Residual plots for compressive strength depicting (a) Normal probability plot in percentage; (b) residual versus fit values; (c) frequency distribution of residuals using histogram; (d) residual versus the order number.

Table 7. ANOVA results for flexural strength of prepared GCC samples obtained from regression analysis.

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
Regression	4	1.06598	99.94%	1.06598	0.266496	1668.50	0.000
A	1	0.03375	3.16%	0.03375	0.033750	211.30	0.000
B	1	0.76327	71.56%	0.76327	0.763267	4778.71	0.000
C	1	0.26882	25.20%	0.26882	0.268817	1683.03	0.000
D	1	0.00015	0.01%	0.00015	0.000150	0.94	0.387
Error	4	0.00064	0.06%	0.00064	0.000160		
Total	8	1.06662	100.00%				

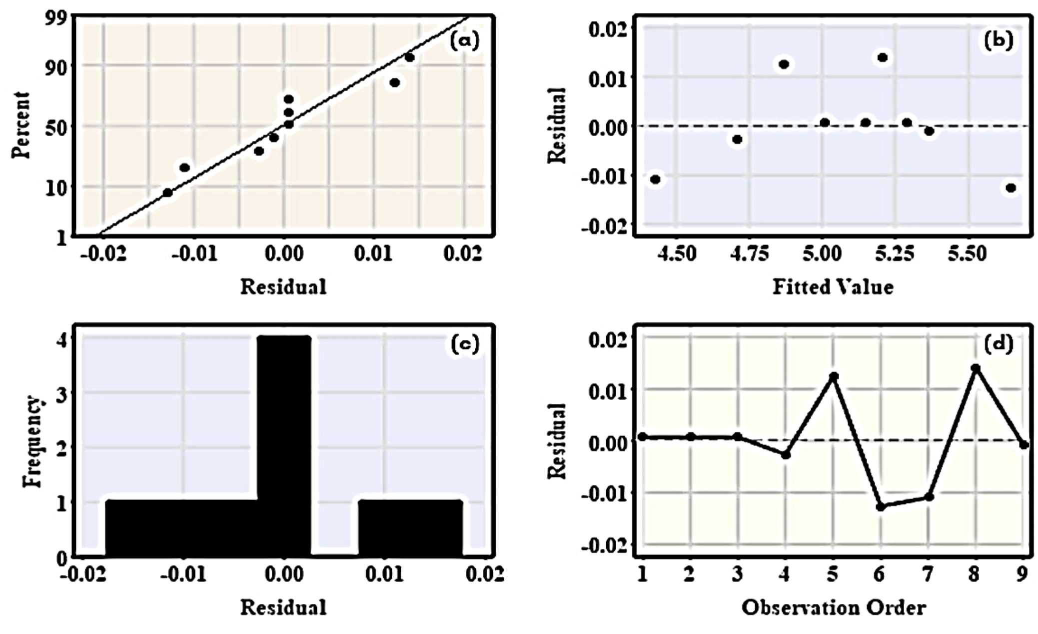

Fig. 6 Residual plots for flexural strength depicting (a) Normal probability plot in percentage; (b) residual versus fit values; (c) frequency distribution of residuals using histogram; (d) residual versus the order number.

Table 8. Summary table for the linear regression analysis of compressive and flexural strength tests.

Response	S	R-sq	R-sq(adj)	R-sq(pred)
Compressive strength	0.131	99.98%	99.96%	99.92%
Flexural strength	0.013	99.94%	99.88%	99.70%

According to the obtained results, the created linear model accounts for 99.98 % of the response variable using Equation 3. The high R^2 score suggests that the model fits the data adequately. The minimal difference in R^2 values between adjusted (99.96%) and projected (99.92%) values shows that the models fit the data extremely well. Furthermore, 'S', the standard deviation, is as low as 0.131.

According to the obtained results, the developed linear model using Equation 4 accounts for 99.94 % of the response variable. A high R^2 score shows that the model adequately fits the data. The minimal difference in R^2 values between the adjusted (99.88%) and projected (99.70%) values shows that the models fit the data extremely well. Additionally, the standard deviation is also as low as 0.013. According to the models illustrated in Equations 3 and 4, both compressive and flexural strengths increase as Factors A, C, and D decrease and Factor B increases.

4. Conclusion

Alkaline-activated cement-based concretes of different mix ratios were tested for the mechanical properties quantified by compression and flexural strength (the response variables). Four factors: A – Sodium hydroxide solution concentration; B – Alkaline liquid to slag mass ratio; C – NaOH to sodium silicate solution ratio and D – Aggregate content were considered the predictor variables. Taguchi's experimental design was used to determine the main effects of the predictor variables on each of the response variables. The linear regression approach, the most basic supervised machine learning method, was implemented to develop the mathematical models to determine the mechanical properties for the given values of predictor variables within the experimental limits. The results obtained indicate that the ratio of alkaline liquid to slag mass, followed by the ratio of sodium hydroxide to sodium silicate solution, is the most significant component affecting the mechanical properties of produced green cement-based concretes as measured by compressive and flexural strengths (GCC). Moreover, from the Taguchi analysis, the T6 combination with a sodium hydroxide solution concentration of 3 M, an alkaline liquid to slag mass ratio of 0.55:1, a NaOH to sodium silicate solution ratio of 1:1, and aggregate content of 1750 kg/m^3 is observed to provide the best mechanical strength of green cement-based composites.

The maximum compressive and flexural strengths are obtained with sodium hydroxide (NaOH) solution at a concentration of 3 M and aggregate content of 1750 kg/m^3. Nonetheless, neither the NaOH concentration nor the aggregate content has a high impact on the strength development of GCC specimens. Also, the compressive strengths of the environmentally friendly green cement-based composites range between 40.04 MPa (T9) and 62.66 MPa (T9) on average (T6). Thus, the average compressive strength of all created GCC exceeds the target value of 40 MPa and could be a great alternative to conventional OPC-based concrete. As a result, it may be stated that this ecologically friendly concrete can be a suitable substitute for conventional Portland cement concrete. The linear regression models developed for compression and flexural strength have strong R^2, adjusted R^2, and anticipated R^2 values. The standard deviation 'S' value is similarly quite low, demonstrating an excellent fit for the experiment's data. Both compressive and flexural strengths are seen to rise as Factors A (concentration of sodium hydroxide solution), C (ratio of sodium hydroxide to sodium silicate solution), and D (aggregate content) are decreased, and Factor B (alkaline liquid to slag mass ratio) is increased.

Conflict of Interest

The authors declare no conflict of interest.

Supporting information

Not applicable.

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