OPTIMIZATION OF EXPERIMENTAL PARAMETERS IN THE BUILDING CONSTRUCTION PROCESS WITH FRACTIONAL FACTORIAL DESIGN AND RESPONSE SURFACE METHODS

ABSTRACT: The study addresses the critical issue of optimizing construction materials to enhance structural integrity, minimize cracks, and prevent building collapses in Nigeria. It utilizes fractional factorial design and response surface methodology (RSM), it also aimed to systematically determine the optimal parameters for concrete mix design to achieve maximum compressive strength. The key factors studied included standard sand size, curing time, water-cement ratio, type of cement, and stone gravel size. The Minitab software was employed to analyse the data, revealing that the type of cement, water-cement ratio, and standard sand size significantly influenced compressive strength. the optimal conditions identified were: Standard sand size of 20 mm, water-cement ratio of 0.5, Bua cement type, stone gravel size of 20 mm, and curing time of 28 days, achieving a predicted compressive strength of 44.175 MPA. the model demonstrated high reliability with an r-squared value of 99.50%. The findings provide valuable insights for enhancing building materials' quality, ensuring structural safety, and reducing the incidence of building failures. This study not only fulfils its aim but also sets a foundation for future research in optimizing construction materials and methodologies.

Index terms: Optimization, construction materials, fractional factorial design, response surface methodology, compressive strength, building safety.

INTRODUCTION

Experiments are typically performed by observing a system or process when a series of inputs are given. In general, the objective of an experiment is to recognize or characterize the output of a system, model the system to predict the output(s), and possibly optimize the system. It is also important to minimize the errors accumulated as part of the experimental process, while trying to speed up the entire process. With more experiments performed, we obtain more data, which makes it easier to properly characterize the system being studied. However, sometimes it is expensive to run the experiment several times, therefore, every run of the experiment should be designed effectively (Montgomery, 2017).

In the factorial design, an experiment is conducted with at least two or more variables, which are called factors. Each factor has certain possible values called levels. The factors used in the experiments are not limited to quantitative values; they could also be qualitative measurements. The factorial design considers the combinations of the levels for the factors investigated.

If the experiments are expensive or the number of factors increases, which leads to an exponential increase in the number of experiments, the number of experiments could be reduced

by running a fraction of the full factorial design. This is called fractional factorial design (FFD). To perform the fractional factorial design, a design generator is needed, which shows how the fractional parts are generated in the fractional factorial design (box and hunter, 1961).
The fractional factor design was originally developed by box and Wilson (1951), in the early 1950s, provided an effective and cost-effective framework for simultaneously investigating the effect of multiple factors and significantly reduced the number of experiments performed.
Fractional factorial design is a statistical technique used to study the effects of multiple variables on a process while minimizing the number of experiments required. It involves selecting a subset of factor combinations (fraction) from the complete factorial design. With this approach, the main and interaction effects of the factors can be assessed efficiently (Montgomery, 2012).
The response surface method (RMS) was introduced by Box and draper (1959) also state that RSM are complementary to FFD by facilitating complex process modeling and optimization. In building construction, RSM can be used to develop predictive models linking input factors to output reactions, identify optimal conditions to minimize construction defects, improve structural integrity, and optimize resource to be used.
The construction industry is a significant contributor to global economic growth and development. With the ever-growing demand for infrastructure and sustainable building solutions, there is an inherent need for continuous improvement in the construction process. One crucial avenue for enhancement lies in the optimization of experimental parameters during the building construction process. This research endeavors to explore this essential aspect of construction through the application of fractional factorial design (FFD) and response surface methodology (RSM) models, with the ultimate aim of achieving efficient resource utilization, cost reduction, and improved structural performance (Simon *et al*, 1999).

2. Statement of the Problem

Optimization of construction materials to minimize building collapses and cracks and improve overall structural integrity is a key challenge in construction engineering. Cracks are not only harmful to aesthetics, but also pose concerns about safety and longevity. To achieve the best material composition and processing conditions to reduce fractures while maintaining structural strength and durability, a systematic approach is required. The complex interactions amongmaterials, environmental conditions, and design specifications require a comprehensive method to effectively address this challenge. In a comprehensive investigation by Uduak *et al* (2018) into the persistent issue of building collapses in Nigeria, it became evident that poor quality building materials and the use of substandard materials play a pivotal role in these disasters. Numerous instances, including collapses in Lagos, Ibadan, Enugu, Abuja, and other regions, were identified as directly attributed to inadequate building materials. Among the 186 recorded cases of building collapses, poor quality materials ranked as the third major cause, underscoring the urgent need to enhance the quality and strength of building materials nationwide. Addressing this critical issue is paramount for ensuring the safety of structures in Nigeria, preserving lives, and safeguarding property. Abed *et al.* (2023) conducted a study on optimizing concrete mixtures to attain the desired compressive strength with minimal material usage. The methodology used is carried out by using appropriate design and analysis of experiments in an empirical way based on a two-factorial central composite design followed by the response surface methodology. The focus is on factors such as water-cement ratio, aggregate size, and curing time. The study focuses on concrete strength optimization; it doesn't directly address the imperative goal of minimizing collapsing and cracking in buildings. The gap lies in the need to consider a wider array of factors (Type of cement, sand, gravels, water cement ratio and curing time) that contribute to collapsing and cracking, beyond just strength enhancement.

3. PROBLEM SOLUTION (METHODOLOGY)

3.1. Experimental

There are five parameters involved in concrete mix design, which are Standard Sand (SS), Curing Time (CT), Water-Cement Ratio (WCR), Type of Cement (TC), and Stone Gravel (SG). Standard Sand has two levels, 16mm and 20mm, representing the particle size of the sand used in the mix. Curing Time varies between 7 days and 28 days, indicating the time period for which the concrete is allowed to harden. Water-Cement Ratio (WCR) includes levels of 0.4 and 0.5, which control the mix's water content relative to the cement. The Type of Cement includes Dangote (450g) and BUA (450g), representing two common brands used. Lastly, Stone Gravel (SG) includes two particle sizes, 16mm and 20mm.All the compositions of five parameters will be mixed together as tabulated in Table 1. In regression modeling or factorial designs, these factors can be coded into levels of -1 and +1, where -1 represents the lower level and +1 represents the higher level. This coding simplifies the statistical analysis by normalizing the variables, making it easier to detect the main, interaction, and quadratic effects among the factors.

Table 1: Design parameters and their levels

Parameters	Level 1	Level 2
STANDARD SAND(SS) PARTICLE SIZE	16mm	20mm
CURING TIME(CT)	7 days	28days
WATER CEMENT RATIO(WCR)	0.4mm	0.5mm

TYPE OF CEMENT(TC)	Dangote (450g)	BUA (450g)
STONE GRAVEL(SG) PARTICLE SIZE	16mm	20mm

Source: BUA cement physical laboratory

3.2The 2^{m-p} design used as a factor screen and response surface methodology

2^{m-p} Fractional Factorial design and Response surface methodology in Design of Experiment (DOE) will be used to screen and find the optimising parameter combination to improve compressive strength of concrete mixture.

The main use of fractional factorial designs is in screening experiments(Montgomery,2017) described screening experiments as tests in which many factors are considered and the objective is to identify those factors that have significant effects.

The Full Factorial Designs or Fractional Factorial Designs are first-degree models and their response equations at two levels have an inherent assumption of linearity.

The response of an experiment could be modelled using an empirical model as

$$y = \mu + \tau_i + \varepsilon \qquad 3.1$$

$$\tau_i = \sum_{j}^{k} \beta_j x_j + \sum_{i} \sum_{<j} \beta_{ij} x_i x_j + ...$$

Where y is the experimental response, μ is the mean population, τ is the treatment effect and ϵ is the experimental error. The treatment effect will correspond to the response of the factors; it will not always have to be linear because it depends on the complexity of the system.

The figure below shows a multivariate linear regression model (that includes interaction terms)based on at two-level factorial design:

$$y = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \sum_{i=1}^{k} \beta_{ij} x_i x_j + \ldots + \sum_{i=1}^{k} \ldots \sum_{j=1}^{k} \ldots \sum_{i=1}^{k} \beta_{ijkl} \ldots x_i x_j x_k x_l .. + \varepsilon$$

Y is the response variable

β_0 Is the mean

β_i Represent the main effect of the factor x_i

β_{ij} Represents the interactioneffect between factors x_i and x_j

$\beta_{i\,jkl}$.... Represent higher-order interaction terms involving factors x_i, x_j, x_k, x_l......

x_i, x_j, x_k, x_l...... Are the levels or settings of the factors.

x_i, x_j Represent the error term.

Response surface methodology is a collection of mathematical and statistical techniques useful for modeling and analyzing problems in which a response of interest is influenced by several variables and the objective is to optimize this response.

For two independent variables, the first order model is given as

$$\eta = \beta_0 + \beta_1 X_1 + \beta_2 X_2 \qquad 3.3$$

This is called a main effect model, because it represents the main effects of two variables X_1 and X_2

If there is an interaction, we have

$$\eta = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_{12} X_1 X_2 \qquad 3.4$$

A second-order model will likely be required in this situation for the case of two variables, which is

$$\eta = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_{11} X_1^{\,2} + \beta_{22} X_2^{\,2} + \beta_{12} X_1 X_2 \qquad 3.5$$

The General first-order model

$$\eta = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots\ldots\ldots + \beta_K X_K \qquad 3.6$$

The General Quadratic Response Surface Methodology (RSM) Model

The model encompasses linear, quadratic and interaction terms for a system with k factors.

$$Y = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \sum_{i}^{k} \beta_{ii} x_i^2 + \sum_{i}^{k} \sum_{j=i+1}^{k} \beta_{ij} x_i x_j + \varepsilon \qquad \textbf{3.7}$$

Where

Y is the response variable

β_0 Is the intercept

β_i Represent the linear coefficient for factor x_i

β_{ii} Represents the quadratic coefficient for factor x_i

β_{ij} Represent the interaction coefficient between factors x_i and x_j

x_i, x_j And x_j are the levels or setting of the factors i and j respectively.

Table 2: Design layout and experiment result

Standard sand	Curing time	Water-cement Ratio	Type of cement	Stone gravels	Compressive strength
16	7	0.4	-1	20	20.8
20	7	0.4	-1	16	19.7
16	28	0.4	-1	16	40.0
20	28	0.4	-1	20	41.5

16	7	0.5	-1	16	19.5
20	7	0.5	-1	20	19.8
16	28	0.5	-1	20	41.3
20	28	0.5	-1	16	42.5
16	7	0.4	1	16	22.9
20	7	0.4	1	20	27.4
16	28	0.4	1	20	41.8
20	28	0.4	1	16	43.0
16	7	0.5	1	20	23.7
20	7	0.5	1	16	27.8
16	28	0.5	1	16	42.0
20	28	0.5	1	20	44.0

Source: BUA cement physical laboratory

4. RESULTS AND DISCUSSION

This section present the result obtained using the method discussed above by using fractional factorial design and response surface methodology.

4.1 Analysis of Variance (ANOVA)

Table 3: Analysis of variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	14	1582.29	113.02	3690.47	0.013

Linear	5	1540.91	308.18	10063.09	0.008
STANDARD SAND	1	11.12	11.12	363.20	0.033
CURING TIME	1	3.85	3.85	125.73	0.057
WATER CEMENT RATIO	1	33.52	33.52	1094.54	0.019
TYPE OF CEMENT	1	1491.89	1491.89	48714.80	0.003
STONE GRAVEL	1	0.53	0.53	17.16	0.151
2-Way Interactions	9	30.11	3.35	109.24	0.074
STANDARD SAND*CURING TIME	1	0.14	0.14	4.59	0.278
STANDARD SAND*WATER CEMENT RATIO	1	6.13	6.13	200.02	0.045
STANDARD SAND*TYPE OF CEMENT	1	0.23	0.23	7.37	0.225
STANDARD SAND*STONE GRAVEL	1	0.77	0.77	25.00	0.126
CURING TIME*WATER CEMENT RATIO	1	0.11	0.11	3.45	0.314
CURING TIME*TYPE OF CEMENT	1	0.77	0.77	25.00	0.126
CURING TIME*STONE GRAVEL	1	4.95	4.95	161.65	0.050
WATER CEMENT RATIO*TYPE OF CEMENT	1	17.02	17.02	555.61	0.027
WATER CEMENT RATIO*STONE GRAVEL	1	0.02	0.02	0.51	0.605
Error	1	0.03	0.03		
Total	15	1582.32			

Table 3 revealed that the model has an f-value of 3690.47 with a p-value of 0.013, indicating that the model is statistically significant and can explain the variability in compressive strength effectively, type of cement ($p = 0.003$) and water cement ratio ($p = 0.019$) are highly significant. Standard sand * water cement ratio ($p = 0.045$) is significant, indicating an interactive effect on compressive strength, curing time * stone gravel ($p = 0.050$) and water cement ratio * type of cement ($p = 0.027$) also show significant interactions, emphasizing their combined impact on strength.

4.2 Optimal Factor Settings

Parameters

Response	Goal	Lower	Target	Upper	Weight	Importance
COMPRESSIVE STRENGHT	Maximum	19.5	44		1	1

Variable Ranges

Variable	Values

STANDARD SAND	(16, 20)
WATER CEMENT RATIO	(0.4, 0.5)
TYPE OF CEMENT	(-1, 1)

Multiple Response Prediction

Variable	Setting
STANDARD SAND	20
WATER CEMENT RATIO	0.5
TYPE OF CEMENT	1

Response	Fit	SE Fit	95% CI	95% PI
COMPRESSIVE STRENGHT	44.175	0.558	(42.933, 45.417)	(41.796, 46.554)

Optimal Compressive Strength: The highest predicted compressive strength is 44.175 MPa at 20 mm standard sand, 0.5 water cement ratio, and BUA cement and Desirability Scores: Solutions 1, 2, and 3 achieve a desirability of 1.00000, indicating that all target criteria are met perfectly. Solutions 4 to 7 also show high desirability, making them practical for implementation.

Table 4 Model Summary

Standard Error(S)	R-squared(R^2)	Adjusted R-Squared(R^2 adj)	Predicted R Squared (R^2 Pred)
0.175	100.00%	99.97%	99.50%

Table 4 Statistical Summary revealed the standard error of 0.175 indicates the average deviation of the observed values from the fitted regression line. This low value suggests that the model fits the data well, with minimal error, R-squared (R^2): 100.00 this perfect value indicates that 100% of the variance in the compressive strength is explained by the model. It suggests that all the factors included in the model are well-represented, Adjusted R-squared (R^2 adj): 99.97%Adjusted R^2, which accounts for the number of predictors in the model, is also very high at 99.97%. This confirms that the model's explanatory power is robust even when considering the number of predictors and Predicted R-squared (R^2 pred): 99.50%, the predicted R^2 value of 99.50% indicates that the model has a high predictive accuracy. This suggests that the model is reliable for predicting the compressive strength of concrete for new data sets.

$$
\begin{aligned}
\textit{Compressive Strength} = {} & 44.77 - 1.888\, SS + 0.1357\, CT - 76.58\, WCR + \\
& 19.642\, TC + 0.2239\, SG + 0.00446\, SS*CT + \\
& 6.188\, SS*WCR - 0.0594\, SS*TC - 0.00729\, SS*SG + \\
& 0.1548\, CT*WCR + 0.02083\, CT*TC - 0.003532\, CT*SG - \\
& 20.625\, WCR*TC - 0.0417\, WCR*SG
\end{aligned}
$$

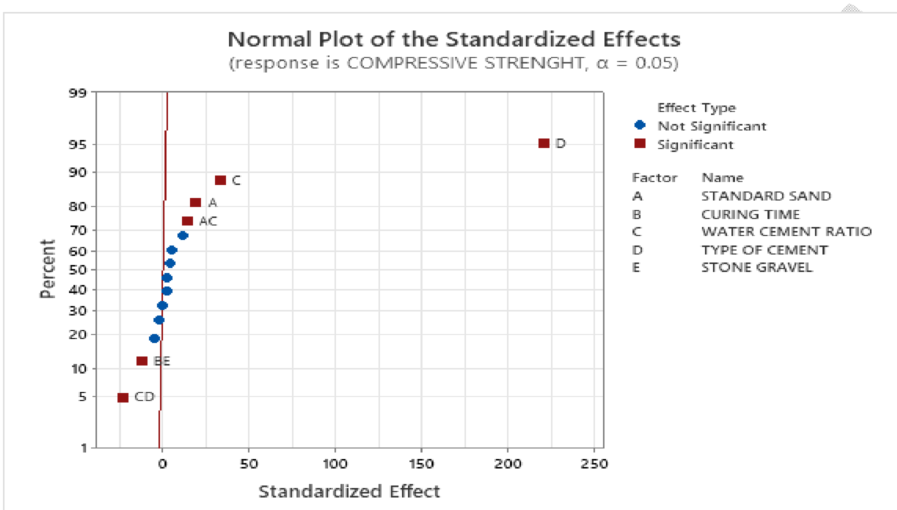

Figure 1: Normal plot of the standardized effects

The above graph is a normal plot of the standardized effects this illustrate that Factor D (Type of Cement) has the strongest positive effect on compressive strength, indicating that the choice of cement type plays a crucial role in determining the strength of the concrete mix. This means that selecting the right type of cement, such as Dangote or BUA, can significantly enhance the compressive strength of the material. The interaction between CD (Water-Cement Ratio × Type of Cement) also shows a significant influence, suggesting that the impact of the water-cement ratio on compressive strength is strongly dependent on the type of cement used. In contrast, Factor C (Water-Cement Ratio) and interactions like AC (Standard Sand × Water-Cement Ratio) are not statistically significant, indicating that their contributions to compressive strength are minimal or negligible under the given experimental conditions. This implies that while the water-cement ratio and sand size are important parameters, their effects may not be as pronounced unless paired with other critical factors such as the type of cement. Therefore, careful consideration should be given to the choice of cement and its interaction with other factors to optimize compressive strength.

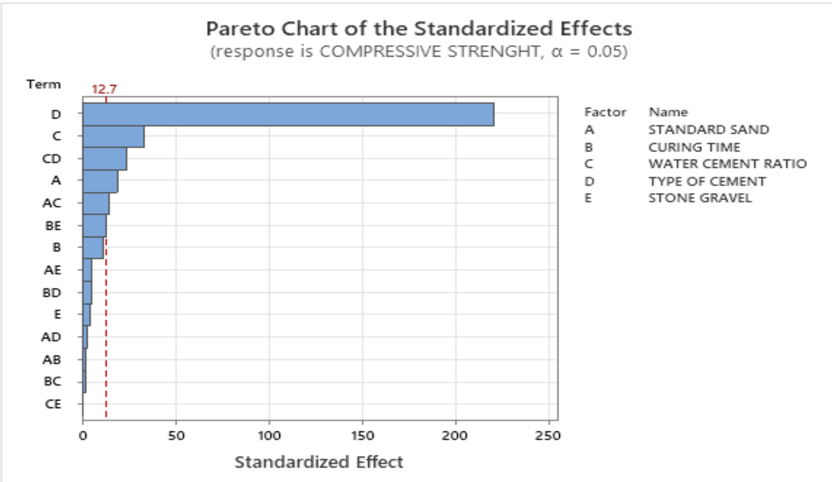

Figure 2: Pareto chart of the standardized effects

The Pareto Chart visually confirms that Type of Cement (D) and the interaction between Water-Cement Ratio and Type of Cement (CD) are the most influential factors affecting compressive strength. The chart effectively ranks the factors based on their impact, showing that optimizing the type of cement and its interaction with the water-cement ratio is crucial for achieving significant improvements in compressive strength. Less significant factors, such as Standard Sand (A), Curing Time (B), and their interactions, are not statistically significant, meaning their effects on compressive strength are minimal. The Pareto chart, an essential tool in quality improvement and experimental analysis, provides a clear visual summary of which factors require the most focus. Based on the chart, attention should be primarily directed toward selecting the appropriate type of cement and managing the water-cement ratio to optimize compressive strength, while other factors may be considered but are unlikely to lead to substantial changes.

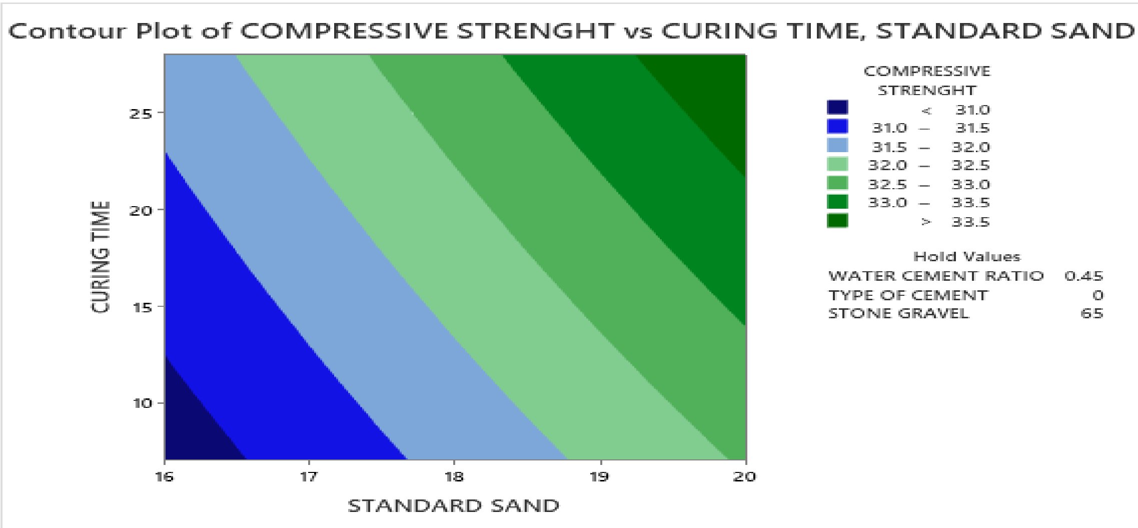

Figure 3: contour plot of compressive strength Vs. curing time, standard sand

The contour plot of "Compressive Strength vs Curing Time, Standard Sand" provides a visual representation of how compressive strength varies with different levels of curing time and the amount of standard sand used in the concrete mix. The x-axis represents the amount of standard sand, ranging from 16mm to 20mm, while the y-axis indicates the curing time, ranging from 7 days to 28 days. The colour gradient in the plot, from blue to green to dark green, indicates varying levels of compressive strength, with blue representing lower strength and dark green representing higher strength.

From the plot, it's clear that compressive strength increases as both curing time and the amount of standard sand increase. The contour lines are relatively parallel and slope upwards from left to right, signifying a strong and positive correlation between these factors and compressive strength. Specifically, at lower sand levels (around 16mm) and shorter curing times (7 days), the compressive strength is significantly lower (blue area) but increases markedly (transitioning through green shades) as either the curing time or sand amount increases.

The steep gradient suggests that even a small increase in either curing time or sand content can lead to a noticeable improvement in compressive strength, especially when both factors are at higher levels (28 days and 20mm, respectively), where the maximum compressive strength is observed. This implies that for optimizing concrete strength, extending the curing period and using a larger amount of standard sand are effective strategies.

The plot clearly indicates that curing time has a slightly more dominant effect on compressive strength than the amount of standard sand, as evidenced by the more pronounced vertical gradient. This suggests that while both factors are important, ensuring sufficient curing time may be more critical in achieving higher compressive strength in concrete mixes.

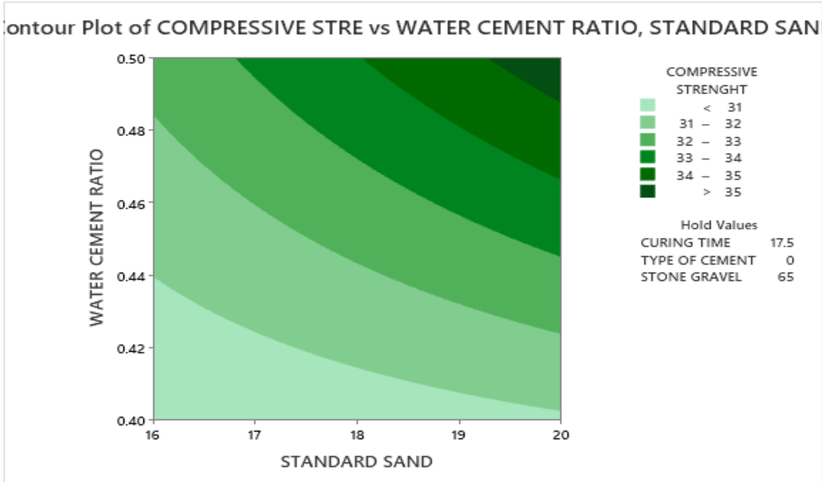

Figure 4: contour plot of compressive strength Vs water cement-ratio, standard sand

The contour plot illustrates the relationship between compressive strength, the water-cement ratio, and the quantity of standard sand in the concrete mix. Lower water-cement ratios (closer to 0.4) generally correspond to higher compressive strengths, as indicated by the darker green regions, while higher ratios lead to lower strengths. The amount of standard sand also positively impacts compressive strength, particularly at lower water-cement ratios, with the plot showing a significant increase in strength as sand content rises from 16 mm to 20 mm. This interaction is more pronounced at lower water-cement ratios, suggesting that increasing sand content has a stronger effect on compressive strength when less water is used. The plot underscores the importance of balancing the water-cement ratio and sand content to optimize compressive strength in concrete, making it a valuable tool for guiding concrete mix formulations in construction. By carefully selecting these factors, one can achieve the desired compressive strength, highlighting the practical implications of this analysis in ensuring the structural integrity of concrete.

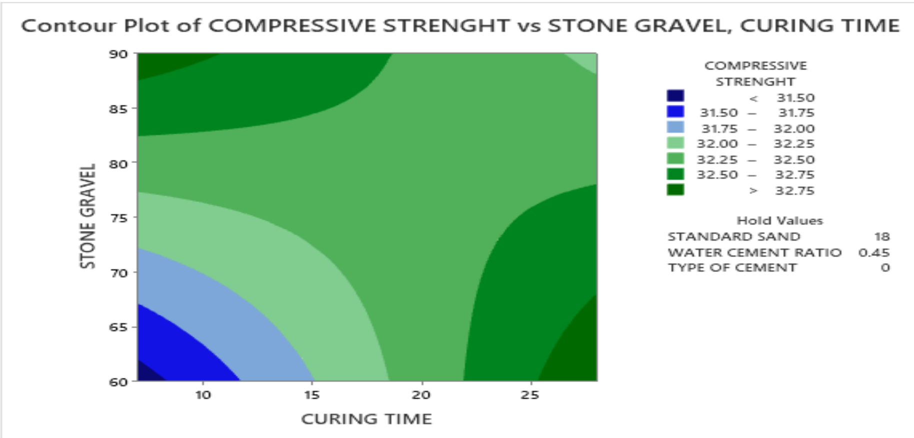

Figure 5: contour plot of compressive strength VS stone gravel, curing time

The contour plot illustrates the relationship between compressive strength, stone gravel size, and curing time in the concrete mix. The plot shows that longer curing times generally lead to higher compressive strengths, as indicated by the darker green regions, especially at curing times closer to 28 days. The size of the stone gravel also impacts compressive strength, with larger gravel sizes (closer to 20 mm) contributing to higher strength levels, particularly when combined with longer curing times. The interaction between these two factors is evident, as the effect of curing time on compressive strength becomes more pronounced with larger gravel sizes. In contrast, at shorter curing times and smaller gravel sizes, the compressive strength is significantly lower, as shown by the lighter green and blue areas. This suggests that for optimal compressive strength, both larger gravel sizes and extended curing times are beneficial. The plot highlights the importance of balancing these factors to achieve the desired concrete strength, making it a practical tool for guiding decisions in concrete mix design, particularly in ensuring that the curing process and gravel size are optimized for structural integrity

5.1 Summary

This study focused on optimizing experimental parameters in the building construction process to enhance structural integrity, minimize cracks, and reduce the risk of building collapses. Through the application of fractional factorial design and response surface methodology (RSM), the study aimed to identify the optimal conditions for achieving maximum compressive strength in concrete, among the factors tested, the type of cement had the most substantial impact on compressive strength, followed by the water-cement ratio, standard sand size, curing time, and stone gravel size and Significant interactions were identified, particularly between standard sand and water-cement ratio, curing time and type of cement, and water-cement ratio with type of cement also the model effectively captures the complex interactions and impacts of various factors on compressive strength. The insights from this model can guide targeted improvements in material selection and mix design, significantly enhancing the structural integrity and durability of building materials lastly The optimal settings for achieving maximum compressive strength were identified as: Standard Sand: 20 mm Water-Cement Ratio: 0.5 Type of Cement:BUA Stone Gravel: 20 mm and Curing Time: 28 days Under these conditions, the predicted compressive strength was approximately 44.175 MPa, demonstrating the effectiveness of the optimized parameters in enhancing concrete strength.

5.2 Conclusion

This study effectively identifies and optimizes the critical factors affecting compressive strength in concrete. its show the Effectiveness of Fractional Factorial Design and RSM in identifying and optimizing the key factors affecting concrete compressive strength. The high R-squared values (99.50% predicted) and significant F-values confirm the robustness and reliability of the model. The critical Factor Type of cement, water-cement ratio, and standard sand size were identified as the most influential factors. Specifically, using BUA cement and maintaining a water-cement ratio of 0.5 were critical for achieving optimal compressive strength. The findings offer valuable insights for enhancing construction materials' quality, safety, and efficiency, contributing significantly to the field of civil engineering.

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