

Modelling and Optimisation of Strength Performance in Self-Compacting Concrete Incorporating Cement Kiln Dust and Superplasticizer



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ABSTRACT: The rising cost of construction materials and the growing demand for sustainability in Civil Engineering have encouraged the use of industrial byproducts as alternative materials. Cement kiln dust (CKD), a waste from cement production, poses environmental disposal challenges but can potentially enhance sustainable concrete production. This study aims to model and optimize the strength performance of self-compacting concrete (SCC) incorporating CKD and varying dosages of superplasticizer (SP) using response surface methodology (RSM). SCC mixes were prepared with CKD replacing cement at 0–25 % and SP dosages of 1.0–2.5 % by weight of cementitious materials, maintaining a water–cement ratio of 0.43 and a mix proportion of 1:2.44:1.48. Mechanical properties, which includes compressive, flexural, and split tensile strengths, were evaluated. Multi-linear regression modelling was used for mathematical modelling. Incorporating CKD content reduced strength, whereas higher SP dosage improved both, workability and mechanical performance. Optimum strengths of 26 N/mm² (compressive), 5.06 N/mm² (flexural), and 3.98 N/mm² (split tensile) were recorded at 10% CKD and 2 % SP. Predictive models achieved high accuracy with R² values of 88.84%, 95.36%, and 94.68%, respectively. Multi-parameter optimization revealed ideal conditions at 15% CKD, 2% SP, and 46 days of curing. CKD can serve as a sustainable supplementary material in SCC, reducing environmental impact and construction costs. For best performance, CKD should be limited to around 10–15 % with 2 % SP dosage.

KEYWORDS: Self-Compacting Concrete, Cement Kiln Dust, Superplasticizer, Design Expert Software, Response Surface Method

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I. INTRODUCTION

Self-compacting concrete (SCC), also known as self-consolidating concrete, is a highly flowable and non-segregating form of concrete capable of filling molds, encapsulating reinforcement, and achieving full compaction under its own weight without external vibration. SCC exhibits exceptional rheological characteristics, representing a major innovation in the construction industry (Dinakar and Manu, 2014). It eliminates the need for mechanical vibration, thereby simplifying concrete placement while ensuring high quality and dense consolidation. In addition to self-consolidation, SCC offers multiple advantages such as enhanced strength, durability, surface finish, aesthetics, and resistance to segregation. Its primary objective is to facilitate the handling and placement of concrete, producing more efficient and durable structural elements by removing the necessity for compaction equipment (Shadkam *et al.*, 2017).

The fundamental characteristics of SCC—resistance to segregation, self-flowing capability, and complete filling of intricate formworks—are achieved through careful mix proportioning in line with EFNARC (2002; 2005) guidelines. These involve optimizing the water-to-powder ratio and aggregate content, supplemented with superplasticizers to ensure workability, self-compactability, and uniformity of the mix. However, a persistent challenge in SCC development is

the lack of a universally accepted mix design procedure (Ma'aruf *et al.*, 2017; Kiran and Nagaraja, 2019; Zeyad, 2020). Since SCC requires high powder content to maintain its rheological properties, relying solely on cement increases cost and the risk of shrinkage or thermal cracking. Partial replacement of cement with supplementary cementitious materials (SCMs) such as fly ash, silica fume, metakaolin, or limestone filler has proven beneficial for improving performance and sustainability (Kannan, 2018). Among potential SCMs, cement kiln dust (CKD), a byproduct of cement manufacturing, constitutes about 3–4% of total cement production and poses disposal challenges. Utilizing CKD in SCC could produce cost-effective and eco-friendly concrete with self-compatibility and enhanced hardened properties due to its pozzolanic characteristics, as previously reported by several researchers.

In concrete research, Response Surface Methodology (RSM) has emerged as a reliable statistical and mathematical tool for modelling and optimizing performance parameters (Haque *et al.*, 2021). RSM enables the development of regression-based models and the use of Analysis of Variance (ANOVA) to optimize independent variables and their interactions (Behera *et al.*, 2018; de la Rosa *et al.*, 2019; Antony, 2022). Using Design Expert software, RSM effectively analyses nonlinear response surfaces to identify optimal parameter combinations

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(Behera *et al.*, 2011; Moodi *et al.*, 2018; Haque *et al.*, 2021). Several studies have demonstrated RSM's applicability in optimizing SCC performance. Eleman *et al.*, (2020) optimized the fresh and compressive strength properties of SCC using fly ash, silica fume, and limestone powder as partial cement replacements. Haque *et al.*, (2021) predicted the properties of SCC containing rice husk ash and glass fibre, achieving optimal values of 16.05% RHA and 0.08% GF through RSM. Patil *et al.*, (2024) applied RSM to fibre-reinforced laterized SCC and experimentally validated model predictions with less than 5% error. Similarly, Clemente *et al.*, (2023) used Central Composite Design (CCD) to optimize cement, water, and superplasticizer contents, achieving SCC mixes that satisfied rheological and strength requirements. Sulaiman *et al.*, (2025) characterised and optimised the concrete properties blended with Sesame Straw Ash as a Partial Replacement of cement by response surface methodology (RSM), and concluded that the optimal composition of 0 % SSA and a curing age of 90 % gave the highest compressive strength of 28.294 MPa, splitting tensile strength of 3.949 MPa and flexural strength of 3.99 MPa respectively. Kelechi *et al.*, (2022) also modelled high-volume fly ash SCC incorporating crumb rubber and calcium carbide residue using RSM, confirming statistical significance for all model reactions ($p < 0.05$).

Therefore, this study aims to model and optimize the strength performance of self-compacting concrete incorporating Cement Kiln Dust (CKD) at varying dosages of superplasticizer (SP) using Response Surface Methodology (RSM). The research specifically evaluates the influence of CKD and SP on the mechanical properties of SCC to establish predictive models and determine the optimal mix proportions for sustainable concrete production.

II. THEORITICAL ANALYSIS

The version 13 (2021) of Design Expert software was utilized for modeling and optimizing the strength properties of the self-compacting concrete.

III. MATERIALS AND METHODS

A. Materials

1) Cement

Portland Limestone Cement (PLC) of grade 42.5N with a specific gravity of 3.15, specifically from the Dangote brand, which was procured from a local vendor at Samaru market.

2) Cement Kiln Dust

The cement kiln dust was collected from a landfill located near a cement manufacturing site in Nigeria, specifically sourced from Obajana in Kogi State.

3) Aggregates

A crushed granite aggregate with a maximum nominal particle size of 20 mm was obtained from Mother Cart Construction Company in Shika, exhibiting a specific gravity of 2.83 and a bulk density of 1417 kg/m³. The fine aggregate was collected from Danja Local Government Area in Katsina State, demonstrating a specific gravity of 2.54 and a bulk density of 1291 kg/m³.

4) Superplasticizer

A polycarboxylate-based ether (PCE) was sourced from the Sabon Gari market.

5) Water

Portable water was collected from the Civil Engineering Department at Ahmadu Bello University in Zaria.

B. Methods

1) Design of Experiment and Development of Mix Design Matrix

The experiment's design was established using design expert software. The mix design was executed through a discrete multi-level categorical factorial experiment. Three factors (independent variables) were taken into account: cement kiln dust, which had six (6) levels (0, 5, 10, 15, 20, and 25 %); superplasticizer with four (4) levels (1.0, 1.5, 2.0, and 2.5 % by weight of cementitious materials); and curing ages with five levels (7, 14, 21, 28, and 56 days). The software generated a mix matrix that included 120 runs with various combinations of the design factors.

$$N = nqr \quad (1)$$

In equation (1), N represents the total number of experimental points, n signifies the levels of the first factor (CKD), q denotes the levels of the second factor (superplasticizer), and r indicates the levels of the third factor (curing age). Following the multilevel factorial design methodology, a total of 120 experimental sets were created to assess compressive, split tensile, and flexural strength.

2) Mix Design

The formulations for self-compacting concrete were created in accordance with the guidelines set forth by EFNARC (2005) and IS 10262 (2019), ensuring a steady water-to-cement ratio of 0.43. This study examined three independent variables: cement kiln dust, which was utilized to partially substitute Portland limestone cement at replacement rates of 0 (control), 5, 10, 15, 20, and 25 %, as well as varying amounts of superplasticizer (1.0, 1.5, 2.0, and 2.5 % based on the weight of the cementitious materials). The concrete was formulated to achieve a target strength of 30 N/mm². Fresh concrete mixtures were created, molded, and cured for durations of 7, 14, 21, 28, and 56 days. In total, twenty-four (24) mixtures were developed for fresh SCC-CKD using various doses of superplasticizer.

3) Determination of Strength Properties of SCC-CKD at Different Dosages of Superplasticizer

a) Compressive Strength

The compressive strength test was conducted following the guidelines of BS EN 12390-2:(2009). Three sets of concrete cubes, each measuring 100x100x100mm, were created and cured for periods of 7, 14, 21, 28, and 56 days. Curing was performed using the immersion method in water until the specified age was reached. After the curing period, each cube was air dried, weighed accordingly, and placed into a testing machine where they were crushed,

b) Flexural Strength

The flexural strength of the SCC-CKD beam was evaluated at varying superplasticizer dosages in accordance with BS 12390-5(2019). Beams measuring 100x100x450mm were constructed and allowed to cure for durations of 7, 14, 21, 28, and 56 days. The flexural strength of these beams was assessed through a three-point bending test. Plate II illustrates the flexural strength testing of the SCC-CKD beams with different superplasticizer quantities.

c) Split Tensile Strength

The split tensile strength of the SCC-CKD with varying amounts of superplasticizer was assessed following the guidelines of BS-EN 12390-6 (2009). Concrete cylinders with dimensions of 100x200mm were produced and cured for periods of 7, 14, 21, 28, and 56 days. The failure load was measured, and the split tensile strength was computed using equation 2.

$$\text{Split tensile strength} = \frac{2P}{\pi LD} \quad (\text{N/mm}^2) \quad (2)$$

4) Mathematical models and Optimization of SCC-CKD at different dosages of superplasticizer

Mathematical models were created based on the strength characteristics of self-compacting concrete. The analysis of variance results indicated the statistical significance of these parameters, as well as the interactions between independent variables and their effects. The models chosen were quantitative, and the significant terms in the regression equations were defined as those with p-values less than 0.05. To evaluate the fit of the dataset with the developed predictive models, metrics such as sum of squares (SS), F-value, probability at a 95 % confidence level (p-value), and the coefficient of determination (R^2) were calculated. Following the fitting of experimental data with the selected models, multivariate equations for the predictive models of SCC-CKD were subsequently formulated. The model equations for the responses were developed based on the general structure of a multiple regression equation.

$$y = b_0 + \sum_{i=1}^k b_i x_i + \sum_{i=1}^k b_{ij} x_i + \sum_{i=1}^{k-1} \sum_{j=i+1}^k b_{ij} x_i x_j + \dots + \varepsilon \quad (3)$$

Where In this context, y represents the predicted response variable, while b_0 , b_i , and b_{ij} denote the respective intercept, model coefficients, and both linear and/or interaction terms, with factors symbolized and representing errors. Design Expert 13 employed numerical optimization to identify the best combination of factors that led to optimal solutions for the desired responses. The necessary criteria for the goals were outlined in relation to both the factors and the corresponding responses.

5) Model Validation

The developed mathematical models were theoretically validated by examining residual plots to confirm that the assumptions for the Analysis of Variance were met. This was achieved through diagnostics, which involved creating plots of externally studentized residuals, such as normal plots, and plots of residuals against predicted values, as well as predicted values against actual values. In addition, experimental validation was performed to verify the precision of the optimization outcomes and the models by using the optimal mix proportions determined through numerical optimization. This was accomplished by calculating the percentage error between the values obtained experimentally and the predicted

values. The variation in percentage error can be calculated with the equation mentioned above.

$$\text{Percentage error (\%)} = \frac{\text{Experimental} - \text{predicted}}{\text{Experimental}} \times 100 \quad (4)$$

IV. RESULTS AND DISCUSSIONS

A. Results of Strength Properties

1) Compressive Strength

The results of the compressive strength for SCC with CKD at varying amounts of superplasticizer is presented in Figure 1.

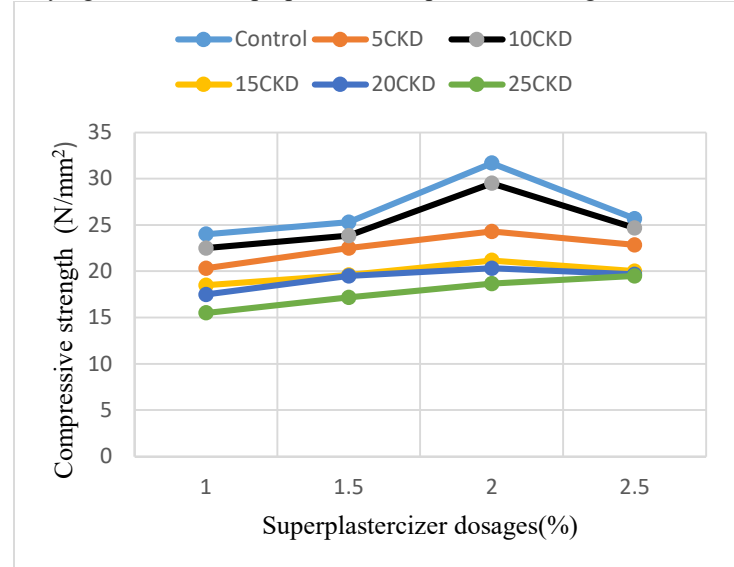


Figure 1 Compressive Strength of SCC-CKD at Different Dosages of Superplasticizer

It was observed that the compressive strength rises as the superplasticizer dosage increases up to 2.0 % SP; however, beyond this level, a slight decrease in the compressive strength was detected for most curves. The decrease may be attributed to an excessive amount of superplasticizer diminishing the cohesion and bonding among the cement particles. The control mix consistently exhibited the highest compressive strength at all dosage levels, reaching a peak of 31.67 N/mm² at 2.0 % SP. The mix that came closest to the control mix was at 10 % CKD and 2.0 % SP, yielding a compressive strength of 29.5 N/mm². Moreover, as the proportion of cement kiln dust increases from 5 % to 25 %, the compressive strength decreases for all dosages of superplasticizer, likely due to a reduction in the content of tricalcium silicate (C₃S) and dicalcium silicate (C₂S), which are vital for cement strength, even though the hydraulic modulus increases with the addition of CKD. Najim *et al.*, (2016) reported similar observations.

2) Flexural Strength

Figure 2 demonstrates the results of flexural strength for SCC-CKD with different levels of superplasticizer.

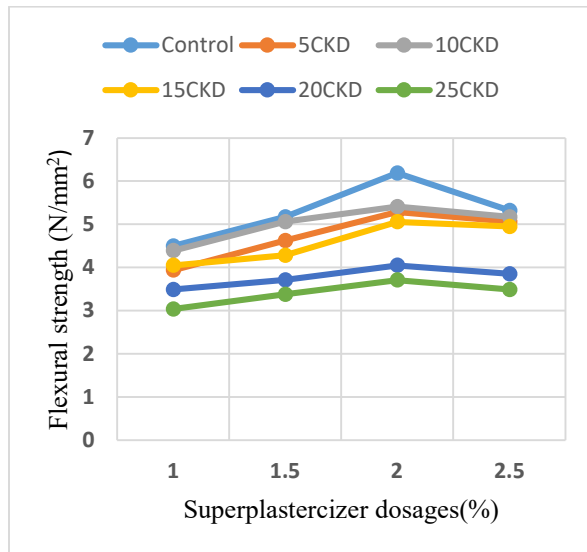


Figure 2 Flexural Strength of SCC-CKD at Different Dosages of Superplasticizer

The control mixture at 0 % CKD exhibited the greatest flexural strength of 6.19 N/mm² when the superplasticizer dosage was set at 2.0 %. Flexural strength consistently increases as the amount of superplasticizer rises to 2.0 %. However, a slight reduction in flexural strength is observed in most instances when the dosage exceeds 2.0 % SP. This decrease in flexural strength beyond 2.0 % SP may be attributed to an overload of superplasticizer that interferes with particle bonding and aggregate cohesion. Furthermore, a higher content of cement kiln dust tends to diminish the flexural strength of the beams, likely due to compromised bonding within the concrete matrix that limits the hydration of cement particles.

3) Split Tensile Strength

Figure 3 displays the results of the split tensile strength tests for SCC-CKD concrete cylinders with different levels of superplasticizer. The control mix consistently exhibits the highest split tensile strength across all dosage levels, peaking at 2.0 % SP. The top measured strength of 4.71 N/mm² occurs at 0 % CKD with 2.0 % SP, while a comparable value of 4.14 N/mm² is seen at 10 % CKD and 2.0 % SP, closely aligning with the control mix.

The split tensile strength continuously increases with higher dosages of superplasticizer, reaching its peak at 2.0 % SP. Once this dosage is exceeded, a notable reduction in split tensile strength is observed in all mixtures, potentially due to the overuse of superplasticizer impairing the concrete mix's internal cohesion, which results in lower tensile strength. Additionally, as the content of cement kiln dust increases (from 5 % to 25 %), the split tensile strength decreases across all levels of superplasticizer. According to Najim *et al.*, (2016), this reduction may be attributed to air voids acting as initiation points for cracks during tensile loading, which accelerates crack formation within the cement matrix, ultimately leading to quicker failure.

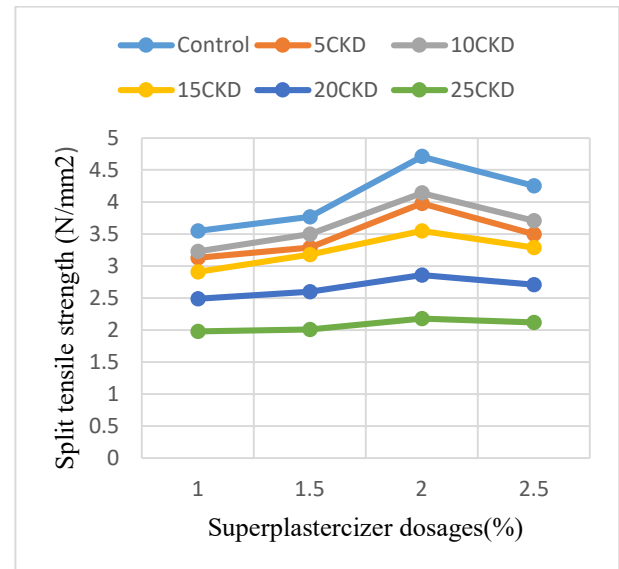


Figure 3 Split Tensile Strength of SCC-CKD at Different Dosages of Superplasticizer

4) Selection of Accurate Predictive Models

Table 1 displays the results of the fit statistics for the created predictive mathematical models. The outcome models assessed are compressive strength, flexural strength, and split tensile strength. The coefficients of determination (R^2), adjusted (R^2), predicted (R^2), and adequate precision for each of the models are provided. The effectiveness of the model can be evaluated using the coefficient of determination (R^2), which serves as a general metric for examining the fitness of a model, as noted by Jadhav *et al.*, (2013) and Haque *et al.*, (2021). The difference between predicted (R^2) and adjusted (R^2) was found to be reasonably aligned, with the variances remaining below 20 % in all instances, as indicated by Haque *et al.*, (2021). Additionally, the adequate precision values, which evaluate the signal-to-noise ratio, were observed to exceed 4. These findings demonstrated sufficient signals, confirming that the models are suitable for forecasting future outcomes.

Table 1 Validity and Accuracy of Developed Predictive Mathematical Models

S/No	Model	Coefficient of Determination R^2	Adjusted R^2	Predicted R^2	Adequate Precision > 4
1	Compressive strength	0.8884	0.8782	0.8631	43.3070
2	Flexural strength	0.9536	0.9469	0.9383	55.2208
3	Split tensile strength	0.9468	0.9409	0.9322	55.9384

5) Analysis of Variance (ANOVA)

In the design of experiments, variance analysis serves to determine if independent variables significantly affect dependent variables. The outcomes of the ANOVA are shown in Tables 2, 3, and 4, which include computed statistical parameters at a 95 % confidence level, a widely used benchmark in statistical analysis. The significance of the coded factors, along with the linear and interaction terms identified in the chosen models, has also been demonstrated

Table 2 ANOVA Results for Compressive Strength of SCC-CKD at Dosages of SP

Source	Sum of Squares	Mean Square	F-value	p-value	
Model	1512.73	151.27	86.78	< 0.0001	significant
C_{kd}	49.95	49.95	28.65	< 0.0001	
S_p	68.22	68.22	39.13	< 0.0001	
C_a	84.01	84.01	48.19	< 0.0001	
$C_{kd} C_a$	34.13	34.13	19.58	< 0.0001	
C_{kd}^2	9.31	9.31	5.34	0.0227	
S_p^2	55.84	55.84	32.03	< 0.0001	
C_a^2	101.01	101.01	57.95	< 0.0001	
C_{kd}^3	7.55	7.55	4.33	0.0398	
S_p^3	27.63	27.63	15.85	0.0001	
C_a^3	26.61	26.61	15.27	0.0002	
Residual	190.01	1.74			
Cor Total	1702.74				

Table 3 ANOVA Results for Flexural Strength of SCC-CKD at dosages of SP

Source	Sum of Squares	Mean Square	F-value	p-value	
Model	77.62	5.17	142.55	< 0.0001	significant
C_{kd}	3.06	3.06	84.28	< 0.0001	
S_p	1.93	1.93	53.04	< 0.0001	
C_a	2.49	2.49	68.63	< 0.0001	
$C_{kd} S_p$	0.3594	0.3594	9.90	0.0022	
$C_{kd} C_a$	1.12	1.12	30.89	< 0.0001	
$S_p C_a$	0.0087	0.0087	0.2386	0.6262	
C_{kd}^2	2.71	2.71	74.73	< 0.0001	
S_p^2	3.68	3.68	101.43	< 0.0001	
C_a^2	1.50	1.50	41.40	< 0.0001	
$C_{kd} S_p^2$	0.3126	0.3126	8.61	0.0041	
$C_a^2 C_{kd}$	0.1449	0.1449	3.99	0.0483	
$S_p C_a^2$	0.2842	0.2842	7.83	0.0061	
C_{kd}^3	0.1476	0.1476	4.07	0.0463	
S_p^3	0.8229	0.8229	22.67	< 0.0001	
C_a^3	0.4270	0.4270	11.76	0.0009	
Residual	3.78	0.0363			
Cor Total	81.40				

Table 4: ANOVA Results for Split Tensile Strength of SCC-CKD at dosages of SP

Source	Sum of Squares	Mean Square	F-value	p-value
Model	47.51	3.96	158.74	< 0.0001 significant
C_{kd}	1.46	1.46	58.36	< 0.0001
S_p	2.00	2.00	80.00	< 0.0001
C_a	1.92	1.92	77.16	< 0.0001
$C_{kd}S_p$	0.1500	0.1500	6.01	0.0158
$C_{kd}C_a$	1.31	1.31	52.47	< 0.0001
S_pC_a	0.1473	0.1473	5.91	0.0168
C_a^2	2.88	2.88	115.27	< 0.0001
S_p^2	0.8003	0.8003	32.09	< 0.0001
C_a^2	1.09	1.09	43.57	< 0.0001
C_{kd}^3	0.5165	0.5165	20.71	< 0.0001
S_p^3	0.9890	0.9890	39.65	< 0.0001
C_a^3	0.5750	0.5750	23.06	< 0.0001
Residual	2.67	0.0249		
Cor Total	50.18			

6) Development of Mathematical Prediction Model

Mathematical forecasting models were developed by analyzing the strength properties of self-compacting concrete mixed with cement kiln dust and different quantities of superplasticizer, utilizing Design Expert 13 to create regression equations for each outcome in both coded and actual forms. Cubic polynomial models yielded the most accurate representation of all responses. Insignificant terms were discarded, resulting in the formulation of the models shown in equations (5), (6), and (7).

$$F_c = 33.407 - 0.2723C_{kd} + 38.225S_p - 0.2034C_a - 0.0037C_{kd}C_a + 0.0184C_{kd}^2 + 27.3153S_p^2 + 0.0223C_a^2 - 0.00061C_{kd}^3 - 5.7227S_p^3 - 0.000290C_a^3 \quad (5)$$

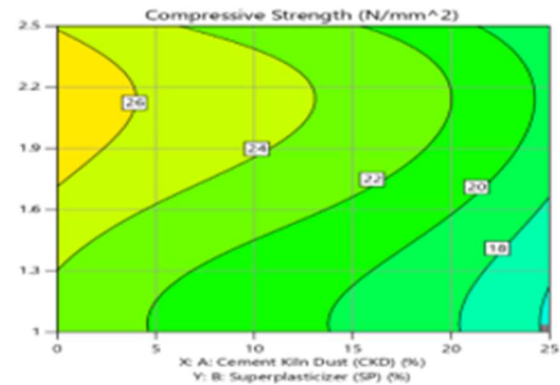
$$F_f = 3.344 + 0.08807C_{kd} - 4.1681S_p + 0.0439C_a - 0.09515C_{kd}S_p - 0.00175C_{kd}C_a - 0.02384S_pC_a - 0.00079C_{kd}^2 + 4.1851S_p^2 + 0.0020C_a^2 + 0.0239C_{kd}S_p^2 + 0.000017C_{kd}C_a^2 + 0.00036S_pC_a^2 - 0.000085C_{kd}^3 - 0.9876S_p^3 \quad (6)$$

$$F_s = 6.228 - 0.0136C_{kd} + 8.0021S_p - 0.0466C_a - 0.0074C_{kd}S_p - 0.00723C_{kd}C_a + 0.0037S_pC_a + 0.00351C_{kd}^2 + 5.3573S_p^2 + 0.0035C_a^2 - 0.0016C_{kd}^3 - 1.0827S_p^3 - 0.000043C_a^3 \quad (7)$$

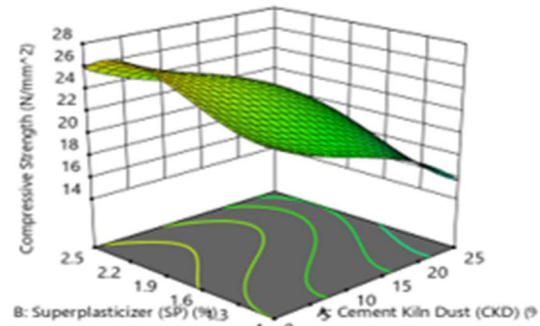
Where C_{kd} , S_p and C_a are coded factors for cement kiln dust, superplasticizer and curing ages respectively, F_c , F_f , F_s are compressive, flexural and split tensile strength of the concrete.

7) Model Graphs

Figures 4, 5, and 6 showcase predictive model graphs (contour and 3D surface) for the compressive strength, flexural strength, and split tensile strength of SCC-CKD across various dosages of superplasticizer. The elliptical patterns observed in the contour plots for all responses suggest strong interactions between the independent variables (factors), as noted by Karim et al. (2013) and Haque et al. (2021).

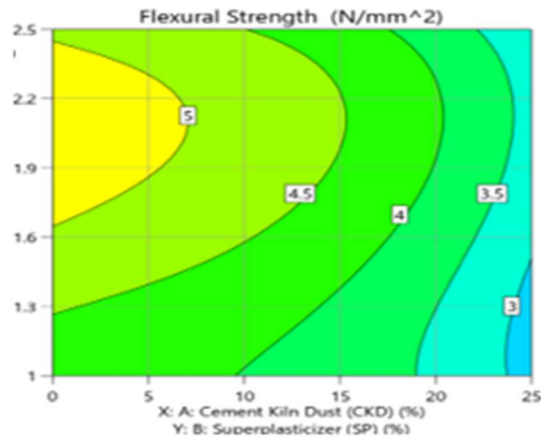


(a)

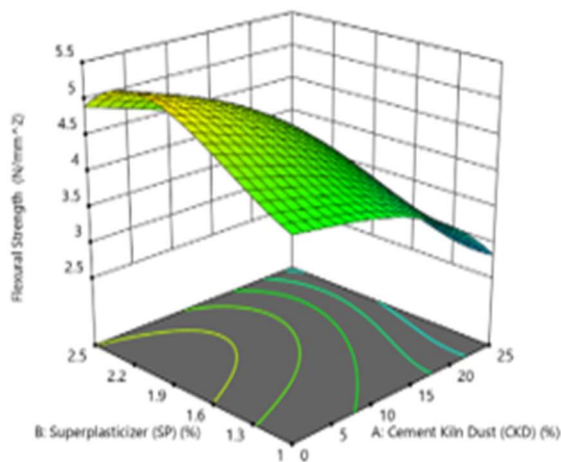


(b)

Figure 4 Contour and 3D plot of compressive strength of SCC at different dosages of superplasticizer (a and b)

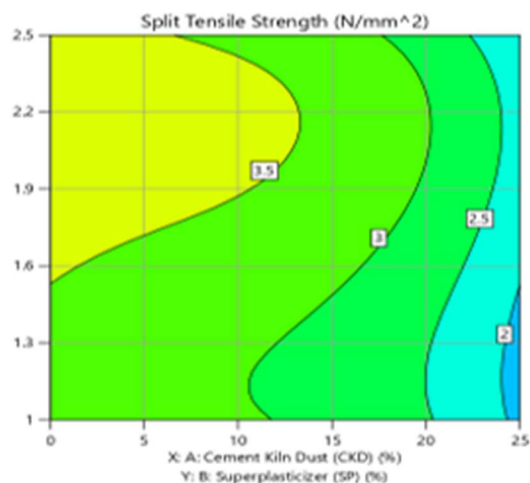


(a)

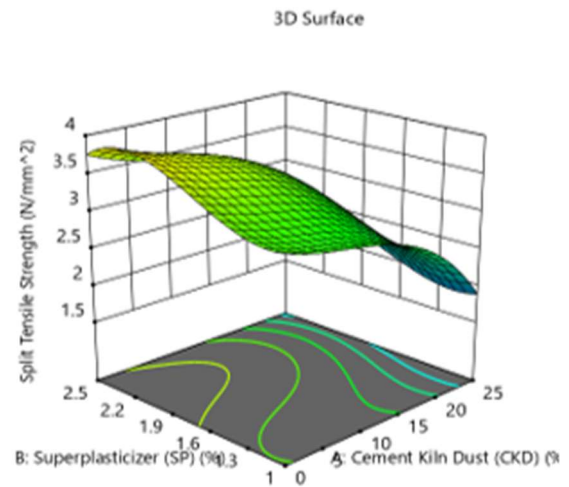


(b)

Figure 5 (a and b) Contour and 3D plot of flexural strength of SCC at different dosages of superplasticizer



(a)



(b)

Figure 6 Contour and 3D plot of split tensile strength of SCC at different dosages of superplasticizer ((a and b)

The contour and 3D surface plots presented in Figures 4 to 6 indicate that the compressive, flexural, and split tensile strength decreases as the amount of cement kiln dust increases. According to Najim et al. (2016), this decline may be due to a reduction in the content of C3S and C2S, which are crucial for cement strength, even though there is an increase in hydraulic modulus with CKD addition. When it comes to flexural strength, higher levels of cement kiln dust led to a reduction in the flexural strength of the beams, likely owing to weaker bonding within the concrete matrix that hinders the hydration of cement particles. The decrease in split tensile strength can likely be explained by the presence of air voids that serve as crack initiation points during tensile loading, causing cracks to propagate more rapidly within the cement matrix, ultimately resulting in quicker failure.

8) Optimization Result of SCC-CKD at different dosages of Superplasticizer

Optimization involves the use of mathematical methods, models, and algorithms to improve a system or design to achieve maximum efficiency. The main goal of optimization is to find the best values for variables that produce the most favourable outcomes. The constraints on the variables and responses are detailed in Table 5.

Table 5 Optimization Constraint

Variables/Responses	Goal	Lower Limit	Upper Limit	Lower Weight	Upper Weight	Importance
A:Cement Kiln Dust (CKD)	Maximize	0	25	1	1	3
B:Superplasticizer (SP)	is in range	1	2.5	1	1	3
C:Curing Age	is in range	7	56	1	1	3
Compressive Strength(N/mm ²)	Maximize	9.67	31.67	1	1	3
Flexural Strength(N/mm ²)	Maximize	2.03	6.19	1	1	3
Split Tensile Strength(N/mm ²)	Maximize	1.27	4.71	1	1	3

Furthermore, the optimization process identified multiple solutions with various combinations of numeric factors and levels of categorical factors. Figure 8 displays the optimized outcomes that produced ideal solutions for the dependent variables (responses). The software explored two possible solutions. It was determined that the optimal solution involves 14.4974% CKD substitution, 2.14995% addition of superplasticizer mixes, and a curing period of 46 days for hardened concrete. This specific combination of factors resulted in optimized outcomes for the responses, achieving 25.8754N/mm², 5.07549N/mm², and 3.85168N/mm² for compressive, flexural, and split tensile strength, respectively. This solution has a desirability value of 0.696. According to Haque et al. (2021), a value closer to one is a clear indication that the optimization objectives have been achieved.

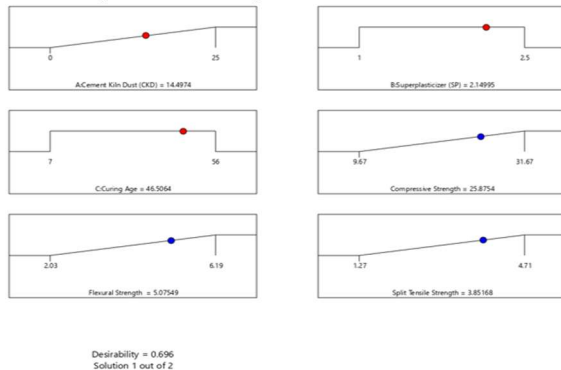


Figure 7 Optimized combination for independent variables and results outcomes for responses (a, b, c, d, e)

The plots displayed in Figures 8(a, b, c, and d) illustrate the desirability and the optimized outcomes for the responses, which include compressive, flexural, and split tensile strength. These plots provide a graphical representation of the optimized solution. In addition, Table 6 presents the summary of the solutions for numerical optimization.

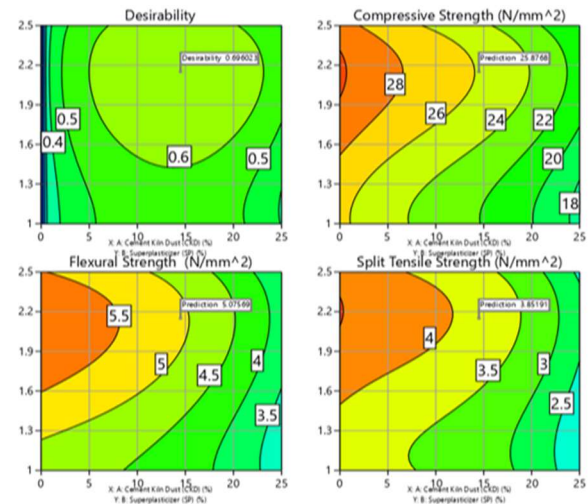


Figure 8 Plots of desirability and optimized results for responses (a, b, c and d)

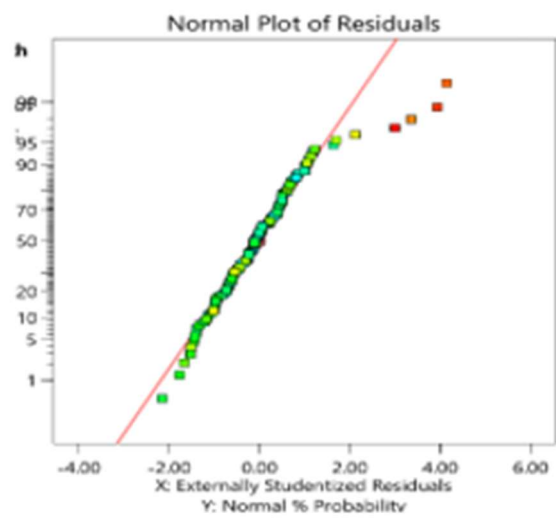
Table 6 Optimization Results of SCC-CKD at different dosages of superplasticizer

S/NO	Cement Kiln Dust (CKD)	Superplasticizer (SP)	Curing Age	Compressive Strength	Flexural Strength	Split Tensile Strength	Desirability	
1	14.497	2.150	46	25.875	5.075	3.852	0.696	Selected
2	13.939	1.000	46	22.236	4.266	3.280	0.562	

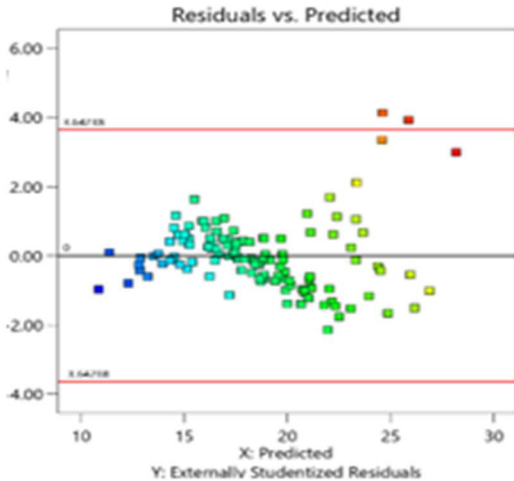
9) Models Validation and Residual Analysis

Figures 9 to 11 display diagnostic plots of the residuals. The illustrations in Figures 9a, 10a, and 11a predominantly demonstrate a clustering of data points around the linear regression line, indicating that the models are appropriate. Following the pencil test, several outliers were detected in all cases, which validates the data's alignment with the predictive models for the outcomes. In Figures 10b, 11b, and 12b, the

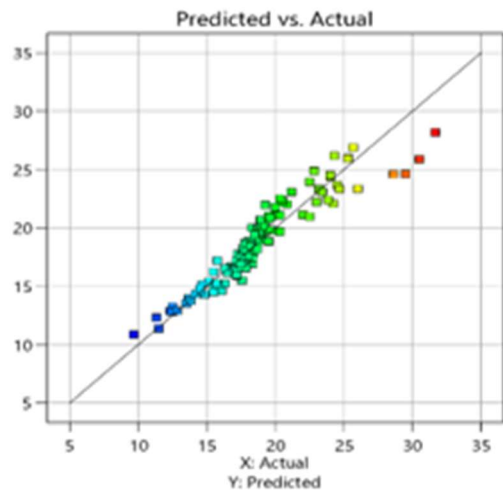
random spread of data points between the upper and lower bounds further confirms the models' suitability for the results. The identified outliers may stem from uncontrollable factors that likely occurred during the experiments. On the other hand, the random distribution of data points along the 450 linear regression lines in Figures 10c, 11c, and 12c suggests that more effective predictive models were selected for all outcomes.



(a)

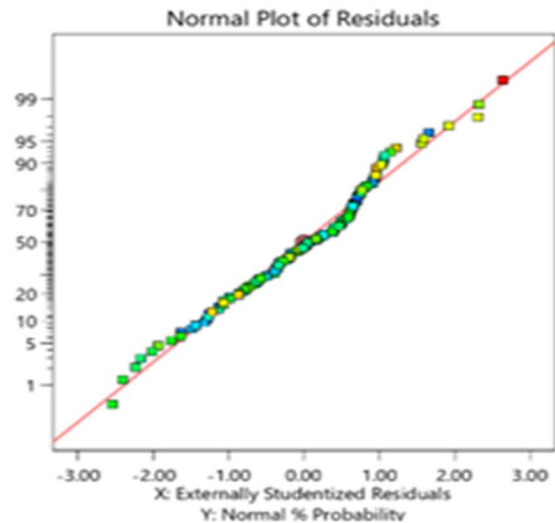


(b)

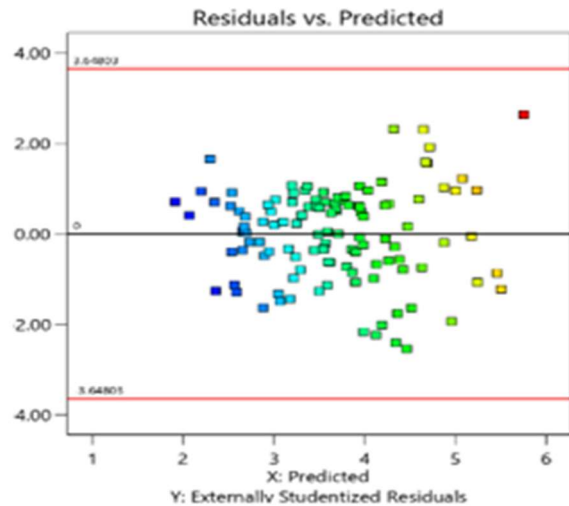


(c)

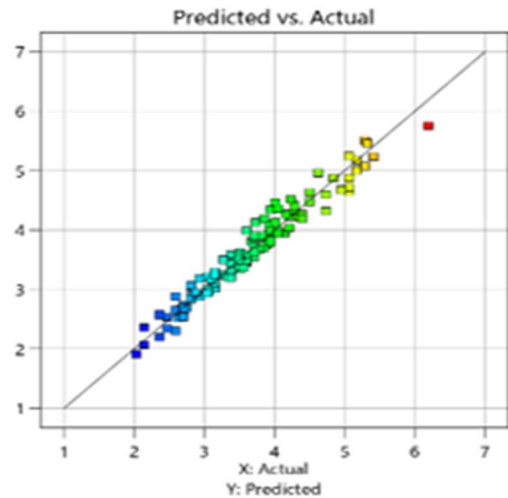
Figure 9 Diagnostics plots of residuals for compressive strength: (a) Normal plot of residuals (b) Residuals vs predicted (c) Predicted versus actual



(a)

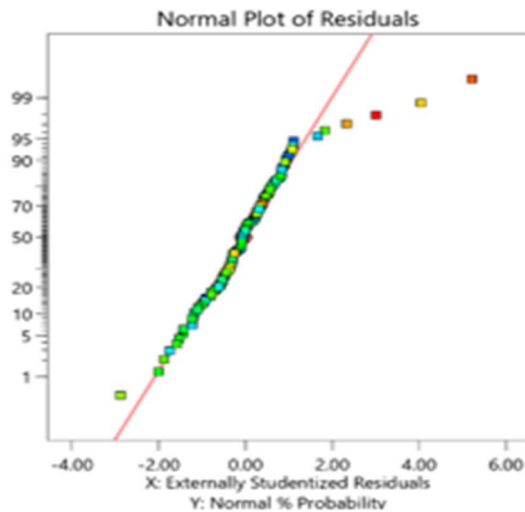


(b)

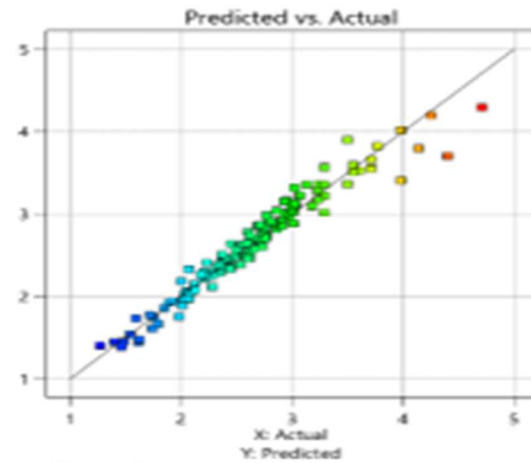


(c)

Figure 10 Diagnostics plots of residuals for flexural strength: (a) Normal plot of residuals (b) Residuals vs predicted (c) Predicted versus actual

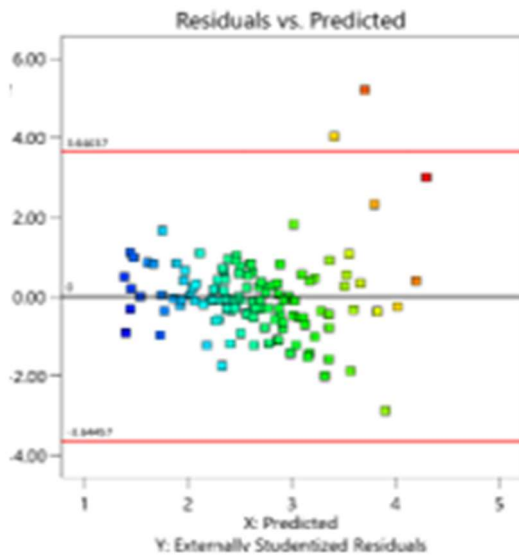


(a)



(c)

Figure 11 Diagnostics plots of residuals for split tensile strength: (a) Normal plot of residuals (b) Residuals vs predicted (c) Predicted versus actual



(b)

10) Experimental Model Validation

The percentage error differences presented in Table 7 showed that nearly all assessed responses fell below 5 %. This indicates that the predicted values from the created models align closely with the experimental outcomes.

Table 7 Experimental Model Validation

Responses	Cement kiln dust (%)	Superplasticizer (%)	Curing Age (days)	Predicted Values	Experimental Values	Error (%)
Compressive strength (N/mm ²)	15	2	46	25.875	26.000	0.481
Flexural strength (N/mm ²)	15	2	46	5.075	5.060	-0.296
Split Tensile Strength (N/mm ²)	15	2	46	3.852	3.750	-2.720

V. CONCLUSIONS

This study modelled and optimized the strength performance of self-compacting concrete (SCC) incorporating cement kiln dust (CKD) and varying superplasticizer (SP) dosages using response surface methodology (RSM). The results revealed that the compressive, split tensile, and flexural strengths of SCC generally decreased with increasing CKD content but

improved significantly with higher SP dosages. The maximum strengths of 29.5 N/mm², 3.98 N/mm², and 5.06 N/mm² were achieved at 10 % CKD and 2.0 % SP, indicating that an optimal balance between CKD replacement and SP dosage enhances both workability and strength performance. The developed mathematical models demonstrated high predictive accuracy, with coefficients of determination (R^2) of 88.84%, 95.36%, and

94.68% for compressive, flexural, and split tensile strengths, respectively. Multi-parameter optimization identified the ideal conditions at 15 % CKD, 2 % SP, and 46 days of curing, producing corresponding strengths of 25.875 N/mm², 5.075 N/mm², and 3.852 N/mm². Model validation further confirmed strong agreement between experimental and predicted values, with percentage errors of 0.481, -0.296, and -2.720, all within the acceptable 5% limit. These findings confirm that the proposed models are reliable tools for predicting SCC performance and demonstrate that CKD can be effectively utilized as a partial cement replacement to produce sustainable, cost-efficient, and high-quality self-compacting concrete.

VI. RECOMMENDATIONS

Based on the experimental results and model analysis, it is recommended that the optimal replacement level of cement with cement kiln dust (CKD) in self-compacting concrete (SCC) should be maintained at approximately 15 %, in combination with a 2 % dosage of superplasticizer (SP) to achieve balanced workability and mechanical performance. These proportions offer a practical guideline for producing sustainable and cost-effective SCC without compromising strength. Furthermore, the developed mathematical models can be effectively utilized for predicting the compressive, flexural, and split tensile strengths of SCC mixtures, provided that the mix parameters, CKD content, SP dosage, and curing age, are clearly defined. The models serve as reliable tools for optimizing SCC design and performance evaluation in both research and practical construction applications.

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AUTHOR CONTRIBUTIONS

I. Garba: Conceptualization, Methodology, Software, Validation & Writing – original draft. Y. D. Amartey: Methodology & supervision. J. M. Kaura: Methodology & supervision. I. Aliyu: Methodology & supervision. T. A. Sulaiman: Review & editing. Y. Yau: Review & editing.

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