Proceedings of the International Conference on Industrial Engineering and Operations Management

Publisher: IEOM Society International, USA DOI: 10.46254/NA11.20260241
Published: June 9, 2026

RSM–Monte Carlo–AHP Optimization of Steel Slag–Sawdust Ash Subgrade Stabilization

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Abstract

Soil stabilization with industrial by-products is increasingly recognized as a cost-effective, low-carbon alternative to conventional chemical binders in developing-country infrastructure. This study proposes an integrated industrial engineering and operations management (IE/OM) framework that combines Response Surface Methodology (RSM), Monte Carlo simulation, and the Analytic Hierarchy Process (AHP) to evaluate Electric Arc Furnace steel slag (SS) and sawdust ash (SDA) for improving lateritic subgrade soils in Osun State, Nigeria. Second-order RSM models were developed for soaked California Bearing Ratio (CBR), Maximum Dry Density (MDD), and Optimum Moisture Content (OMC) across nine mix configurations, achieving high in-sample fit (R^2 = 0.996–0.997), indicative of parametric efficiency at small sample size (n = 9). Leave-One-Out Cross-Validation yielded an indicative Q^2 = 0.956

(RMSE = 2.55 pp), though further validation is required. Optimization identified a provisional optimum at 20% SS and 6.6% SDA (predicted CBR = 58.0%). Monte Carlo simulation incorporating dosing variability and model residuals produced an indicative process capability (Cpk = 1.50). Complementarily, AHP—using literature-informed stakeholder weights—ranked 15% SS and 7% SDA as the preferred blend (score = 0.848). The framework is therefore presented as a transferable proof-of-concept decision-support tool, with its quantitative outputs interpreted as indicative pending validation through larger replicated designs, soil-specific modelling, stakeholder elicitation, and field-scale trials.

Keywords
Response surface methodology; Monte Carlo simulation; Analytic Hierarchy Process; Subgrade stabilization; Steel slag; Sawdust ash

1. Introduction
Road infrastructure quality is a primary determinant of economic productivity in sub-Saharan Africa. Improving rural road connectivity raises crop production and stimulates market integration, particularly in remote areas with high travel-time costs to urban centres (Berg et al., 2018). In Nigeria, pavement failures are frequently traceable to inadequate subgrade performance. Subgrade soils in Osun State — predominantly lateritic, plastic, and moisture-sensitive — exhibit liquid limits exceeding 50% and soaked CBR values near or below the 7% minimum specified in the Nigerian Federal Highway Manual (Federal Ministry of Works, 2013). The conventional stabilization using Portland cement is effective but economically burdensome and associated with a high embodied carbon footprint.
Two categories of industrial waste accumulate in southwestern Nigeria with limited beneficial reuse: Electric Arc Furnace (EAF) steel slag (SS) from regional steel plants and sawdust ash (SDA) produced by timber-processing operations. Both materials possess geotechnically favourable properties — SS provides high-friction coarse particles and reactive CaO/SiO_2; SDA contributes fine pozzolanic material that fills inter-particle voids and forms cementitious hydrates in the presence of moisture (Etiegni and Campbell, 1991; Irem and Monica, 2011). Their co-deployment simultaneously addresses industrial waste management burdens and reduces road construction costs, a configuration aligned with circular economy principles increasingly embedded in Nigerian infrastructure policy (Oluwatuyi et al., 2019; Yildirim et al., 2022).

The present paper applies three IE/OM methodologies to an existing laboratory dataset: (i) RSM to map the design space and identify an indicative optimum; (ii) Monte Carlo simulation to propagate uncertainty and estimate process capability; and (iii) AHP to structure multi-stakeholder blend selection. Leave-One-Out Cross-Validation and a Random Forest comparison are included to assess model selection (Zhang et al., 2022; Kardani et al., 2023). The study is explicitly scoped as a proof-of-concept methodological framework. The methodological template is replicable and presented with sufficient transparency to support its application to larger, better-replicated datasets in future work.
This paper makes three contributions to the IE/OM literature. First, it provides a methodological contribution: a replicable RSM–LOOCV–Monte Carlo–AHP pipeline for material process optimization that is transferable to any small designed experiment in geotechnical or construction engineering, with explicit guidance on handling small-sample limitations. Second, it provides a domain-specific contribution. Laboratory results show that co-stabilization using EAF steel slag and sawdust ash consistently exceeds the Nigerian Federal Highway minimum CBR threshold (Federal Ministry of Works, 2013). This is observed across three lateritic soils in Osun State. The study also presents a structured method for selecting optimal blends. This selection is based on clearly defined multi-stakeholder priorities. Third, it offers a practical contribution. A decision-support matrix will help road agencies select blend proportions based on defined reliability targets. It also introduces Cpk as a simple and useful process quality metric for field engineers. Together, these contributions form a proof-of-concept demonstration. They confirm that IE/OM quality-engineering tools can be systematically applied to sustainable infrastructure material selection. It is especially relevant in data-limited, developing-country contexts. Accordingly, the principal contribution is methodological rather than prescriptive: the study demonstrates how IE/OM quality-engineering tools can structure material-selection decisions under data scarcity, while recognizing that design-level recommendations require larger replicated datasets and field validation.

The remainder of the paper is structured as follows: Section 2 reviews relevant literature. Section 3 describes materials and methods. Sections 4–7 present results. Section 8 provides an integrated critical discussion. Section 9 states conclusions and future work priorities.

2. Literature Review and IE/OM Framing

2.1 Subgrade Stabilization with Industrial By-Products

Bowles (1992) classifies subgrade quality by compressive strength; AASHTO and SUDAS (2013) rate subgrade CBR from very poor (<3%) to excellent (>20%). Geiman (2005) reported that chemical treatment can raise in-situ CBR to 12–30 times untreated values. Irem and Monica (2011) established the chemical and mineralogical properties of EAF slag and demonstrated CBR improvement when BOF slag was combined with Class C fly ash. Ebenezer et al. (2014) confirmed steel slag suitability for road construction, noting high internal friction and non-heaving behaviour. Biradar et al. (2014) showed that combined steel slag and fly ash produced CBR improvements of up to 180% over untreated clay soils. Luckman et al. (2008) described the cementitious and pozzolanic mechanisms by which EAF slags contribute to strength gain.

For SDA, Etiegni and Campbell (1991) characterised wood ash as predominantly SiO_2- and CaO-rich, satisfying pozzolanic activity thresholds. Amu et al. (2005) demonstrated that wood ash co-treatment improved CBR and reduced plasticity of lateritic soils in southwestern Nigeria. More recent work confirmed that industrial by-product binders can simultaneously reduce plasticity and improve strength across varying soil classifications (Oluwatuyi et al., 2019). Yildirim et al. (2022) and Firoozi et al. (2023) further demonstrated that alkali-activated slag systems achieve CBR values suitable for primary rural road bases while offering meaningful reductions in lifecycle carbon relative to Portland cement, providing direct motivation for the circular-economy framing adopted here.

2.2 Response Surface Methodology in Geotechnical Engineering

RSM — originally developed by Box and Wilson (1951) and comprehensively presented by Montgomery (2017) — has been applied to geotechnical stabilization optimization by Turkane and Chouksey (2022), Wang et al. (2023), and Shen et al. (2024). A recurring limitation in these applications is the exclusive reporting of in-sample R^2, which describes fit rather than predictive validity. The present paper addresses this gap by reporting LOOCV Q^2 alongside in-sample R^2, and explicitly acknowledges the instability of LOOCV at $n = 9$.

2.3 Monte Carlo Simulation and Process Capability

Monte Carlo simulation propagates input uncertainty through a system model to characterize the output distribution (Law, 2015). Process capability indices (Cpk) quantify the relationship between process variability and specification limits; Cpk $\geq$ 1.33 is the industry standard for a capable process (Montgomery, 2009). Rashid et al. (2022) demonstrated that dosing-only Cpk estimates systematically overstate capability when model residual uncertainty is omitted, by factors of 2–5 when R^2 is moderate. The present study incorporates residual uncertainty following this approach (Rollings and Rollings, 1996), and additionally notes that Cpk estimates are sensitive to distributional assumptions.

2.4 Analytic Hierarchy Process for Multi-Stakeholder Decisions

The AHP (Saaty, 1980) derives criterion weights from pairwise comparisons and synthesizes alternative scores into a composite priority vector. It has been widely applied in infrastructure planning and construction material selection (Dey, 2002; Zavadskas et al., 2014; Adeleke et al., 2023). A known limitation is the subjectivity of pairwise comparisons when empirical stakeholder elicitation is not performed. The present study addresses this by grounding criterion weights in published priorities from Adeleke et al. (2023) and explicitly labelling the AHP as hypothetical pending formal expert survey validation.

2.5 Machine Learning Benchmarks for Small Geotechnical Datasets

Random Forest and gradient boosting models have been applied to geotechnical property prediction with strong training-set R^2 on datasets of $n \geq 100$ (Zhang et al., 2022; Kardani et al., 2023). On small designed experiments ($n < 20$), ensemble methods overfit severely, with LOOCV RMSE typically 2–3× worse than parametric RSM. Including an RF comparison at $n = 9$ in the present study is illustrative of the parametric efficiency argument for RSM rather than a general benchmark of predictive accuracy.

3. Materials and Experimental Methodology

3.1 Soil Samples and Additives

Three subgrade soil samples were collected at 0.5–1.5 m depth from three locations in Osun State, Nigeria: Sample A from Ajebandele road (silty sand, SM per USCS); Sample B from Tonkere road (clayey sand, SC); and Sample C from Osu Road (clayey sand, SC). AASHTO classification placed all three in the A-2-7 to A-2-5 subgroups. Baseline

soaked CBR values of 30.51%, 7.45%, and 30.66% for Samples A, B, and C respectively indicated that Sample B barely met the Nigerian Federal Highway minimum threshold of 7% (Federal Ministry of Works, 2013), making it the critical risk soil. The three soils span two USCS classifications (SM and SC); the decision to fit a single averaged RSM surface across these soil types is a methodological simplification with implications discussed in Section 8.
EAF steel slag was obtained from Ife Iron and Steel Company, Ile-Ife, ground using a hammer mill, and sieved to two gradations: passing 1180 µm (No. 14 sieve) for engineering property tests, and passing 425 µm (No. 36 sieve) for index property tests. Sawdust from a local timber yard was combusted under controlled conditions; the resulting ash was sieved to passing 425 µm and stored in sealed containers. PIXE analysis confirmed Si, Al, and Fe in the soil samples; CaO, FeO, and SiO_2 in EAF slag; and Si, Ca, and K in SDA, consistent with pozzolanic classification criteria (Etiegni and Campbell, 1991; Irem and Monica, 2011).

3.2 Geotechnical Testing Program

Nine mix proportions (SS at 5–20% and SDA at 3–10% of SS weight) were evaluated on all three soils, generating 27 observations each of CBR, MDD, and OMC. No true replication was performed within any mix proportion. All tests followed BS 1377 and ASTM D standards. For RSM fitting, per-proportion averages across the three soils were used, yielding n = 9 observations per response variable.

This data structure is adequate for demonstrating the analytical workflow but not for deriving final construction specifications; the resulting models are therefore interpreted as regional indicative surfaces rather than validated soil-specific prediction tools. This averaging procedure intentionally produces a regional approximation model — describing the central tendency of the SS–SDA stabilization effect across the Osun State lateritic soil population — rather than a soil-specific predictive model. This is a deliberate analytical choice consistent with the proof-of-concept scope; its limitations are discussed in Section 8.3.

3.3 IE/OM Analytical Framework

The analytical sequence was: (i) RSM second-order OLS fitting and differential evolution optimization; (ii) LOOCV and Random Forest comparison to assess model selection (Bowles, 1992; Montgomery, 2017); (iii) Monte Carlo simulation (N = 50,000) to propagate dosing variability and RSM residual uncertainty; and (iv) multi-stakeholder AHP with hypothetical weights grounded in Adeleke et al. (2023). All computations used Python (NumPy, SciPy, scikit-learn). The analytical sequence is intentionally framed as a proof-of-concept pipeline: RSM, LOOCV, Monte Carlo simulation, and AHP are used to show how uncertainty-aware material selection can be organized when experimental data are limited.

4. Response Surface Methodology and Optimization

4.1 Model Specification and Fitting

A second-order polynomial response surface model was fitted to each response variable by Ordinary Least Squares, averaged across the three soil samples (Box and Wilson, 1951; Montgomery, 2017). Readers are advised at the outset that with six parameters estimated from nine observations, only three residual degrees of freedom are available. Near-unity R^2 values are therefore a mathematical consequence of the model structure rather than evidence of genuine predictive accuracy; all quantitative outputs in this section should be treated as indicative proof-of-concept values pending replication on larger datasets (see Sections 5 and 8.2).

$$\hat{y} = B_0 + B_1X_1 + B_2X_2 + B_{11}X_1^1 + B_{22}X_2^2 + B_{12}X_1X_2 \quad (1)$$

where x_1 is the SS content (% by dry soil weight) and x_2 is the SDA content as a proportion of SS (%). With six parameters estimated from nine average data points, only three degrees of freedom remain for residual error; coefficient estimates should be interpreted cautiously. Table 1 reports fitted coefficients and goodness-of-fit. The RSE for the CBR model is 1.40 pp; Section 5 examines whether this fit reflects genuine predictive structure.

Table 1. RSM Coefficient Estimates and Goodness-of-Fit

Response	B_0	B_1 (SS)	B_2 (SDA)	B_{11}	B_{22}	R^2
CBR(s) avg (%)	25.90	1.73	−3.92	−0.087	−1.097	0.996

MDD avg (kg/m^3)	1608.6	−8.27	53.99	0.404	−7.116	0.997
OMC avg (%)	24.72	−0.293	−1.190	0.006	−0.299	0.987

Note: Interaction coefficient B_{12} (SS × SDA) = 0.789, 1.259, and 0.200 for CBR(s), MDD, and OMC respectively. With only 3 residual degrees of freedom, the interaction estimate for CBR should be treated as indicative pending replication.

4.2 Optimization and Design Lookup

Differential evolution optimization was applied to the fitted CBR(s) surface within the feasible region (SS: 0–20%, SDA: 0–10%). The algorithm identified an indicative optimum at SS = 20%, SDA = 6.6%, with predicted CBR(s) = 58.0%, substantially exceeding both the Nigerian Federal Highway minimum (7%; Federal Ministry of Works, 2013) and the SUDAS good-quality subgrade threshold (20%) (SUDAS, 2013). The SUDAS threshold is a US standard applied here as an internationally recognised benchmark for comparative purposes; it does not replace the Nigerian Federal Highway specification as the primary regulatory criterion. Table 2 presents predicted values at representative design points.

Table 2. Predicted CBR(s) (%) at Key Design Points from RSM Model

SS% / SDA%	**0% SDA**	**3% SDA**	**5% SDA**	**7% SDA**	**10% SDA**
5% SS	32.4	22.6	14.2	4.6	−8.5 (e)
10% SS	34.5	36.5	36.4	30.4	13.8
15% SS	32.2	46.1	49.8	43.1	28.6
20% SS (opt.)	25.6	51.3	58.0 *	54.9	41.0

** RSM-predicted indicative optimum. (e) Extrapolation outside the calibrated design space; values are physically non-meaningful and should not be used for design. Approximate 95% prediction intervals ≈ ±3.5–4.5 pp within the design space.*

4.3 RSM Contour Map and Response Surface

Figure 1 presents the RSM contour map and three-dimensional response surface. The feasible design region (CBR(s) ≥ 20%) expands substantially at SS contents above 15%, indicating that SS dosage is the dominant driver of CBR performance in this dataset. The curvature of the contours in the upper-right quadrant is consistent with an SS × SDA interaction (Luckman et al., 2008), though this interaction is estimated with limited precision given the small dataset.

4.4 Sample B: Critical Risk Soil

Sample B (Tonkere road, CBR = 7.45% untreated) is the most practically critical soil — the only one that barely meets the Nigerian Federal Highway minimum of 7% (Federal Ministry of Works, 2013) and the one for which stabilization is most clearly necessary. At the SUDAS 20% comparative threshold, Sample B requires at least 15% SS for likely compliance. This finding is consistent with the AHP recommendation of 15% SS + 7% SDA discussed in Section 7.

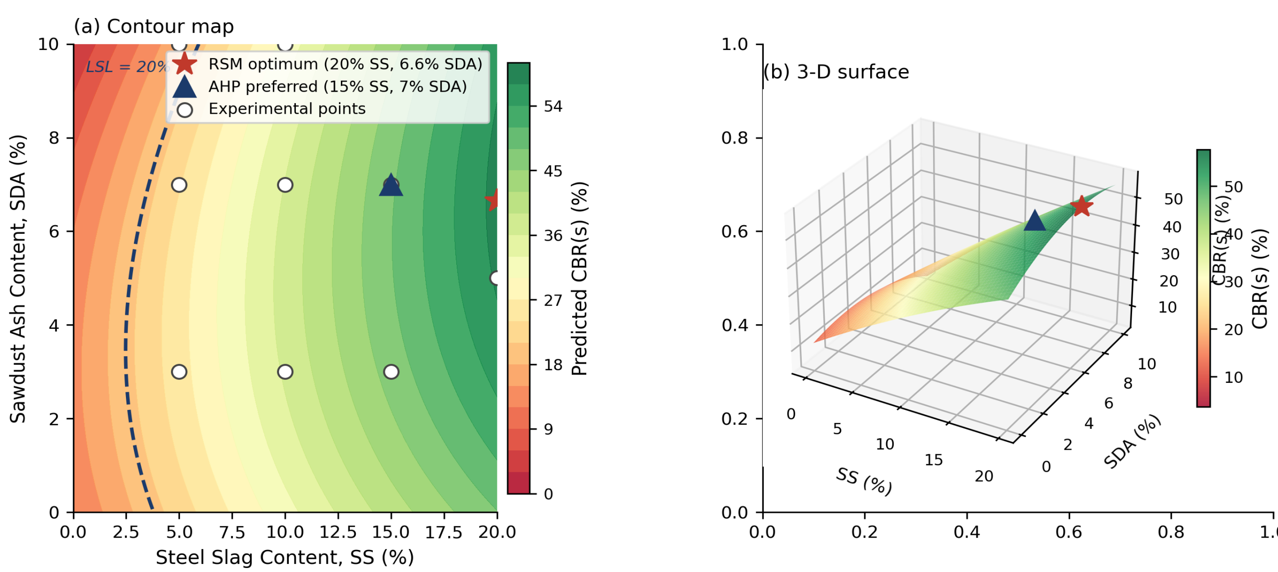

Figure 1. RSM contour map and three-dimensional response surface for predicted soaked CBR(s). (a) Contour map: navy dashed line = SUDAS 20% lower specification limit; hatched region = extrapolation zone; red star = RSM indicative **optimum (20% SS, 6.6% SDA); blue triangle = AHP-preferred blend (15% SS, 7% SDA); open circles = experimental design points. (b) 3-D surface.**

5. Model Validation: LOOCV and Random Forest Comparison

5.1 Rationale and Scope

The model validation exercise serves a specific, bounded purpose: to assess whether the RSM model contains genuine predictive structure or merely interpolates the nine averaged data points, and to justify the choice of RSM over ensemble ML methods for this dataset size. It does not constitute full external validation of the model predictions. With n = 9, LOOCV is itself a small-sample procedure: Q^2 estimates are unstable, and even $Q^2 = 0.956$ could arise from a well-fitting curve through a small, well-behaved dataset rather than from a genuinely generalizable relationship. This limitation is acknowledged explicitly.

5.2 Leave-One-Out Cross-Validation

LOOCV iteratively withholds each of the nine observations, refits the model on the remaining eight, and predicts the withheld point. The predictive Q^2 is:

$$Q^2 = 1 - \sum \frac{\sum(y_i - \hat{y}_i LOO)^2}{\sum(y_1 - \bar{y})^2} \quad (2)$$

The RSM CBR model yielded $Q^2 = 0.956$ and RMSE = 2.55 pp. This suggests the model contains predictive structure beyond in-sample interpolation. However, given n = 9, this Q^2 should be treated as indicative rather than conclusive: each LOOCV fold leaves only eight points to refit six parameters (two residual degrees of freedom), meaning individual fold predictions are themselves highly uncertain.

Thus, LOOCV is used here as a diagnostic check on model structure rather than as a substitute for external validation.

5.3 Residual Diagnostics

Figure 2b presents residuals versus fitted values; no systematic curvature or fan pattern is apparent, suggesting no gross structural misspecification in this dataset. Figure 2c presents the normal Q-Q plot of residuals (r = 0.97), supporting approximate normality of the residual distribution. These diagnostics are encouraging but based on nine data points, and their power to detect misspecification is accordingly limited.

5.4 Random Forest Comparison

A Random Forest model (200 trees, scikit-learn defaults) was evaluated under identical LOOCV conditions (Zhang et al., 2022; Kardani et al., 2023). Table 3 summarises results. RF achieves near-perfect in-sample $R^2 = 0.999$ — direct evidence of training-data memorisation — while LOOCV RMSE rises to 6.23 pp and Q^2 falls to 0.737. This outcome was expected a priori: at n = 9, an ensemble with hundreds of trees has far more capacity than data can constrain. The comparison is therefore illustrative of the parametric efficiency argument for RSM on small designed experiments, not a general benchmark of the two methods. The same Random Forest would very likely outperform RSM given n ≥ 100 observations with genuine soil-specific variation.

Table 3. In-Sample and LOOCV Predictive Performance: RSM vs Random Forest (n = 9)

Model	**In-sample R^2**	**LOOCV RMSE (pp)**	**Q^2 (predictive R^2)**	**n**	**Interpretation**
RSM (2nd-order polynomial)	0.996	2.55	0.956	9	Parametric model preferred at n = 9
Random Forest (200 trees)	0.999	6.23	0.737	9	Overfits; not recommended at n = 9

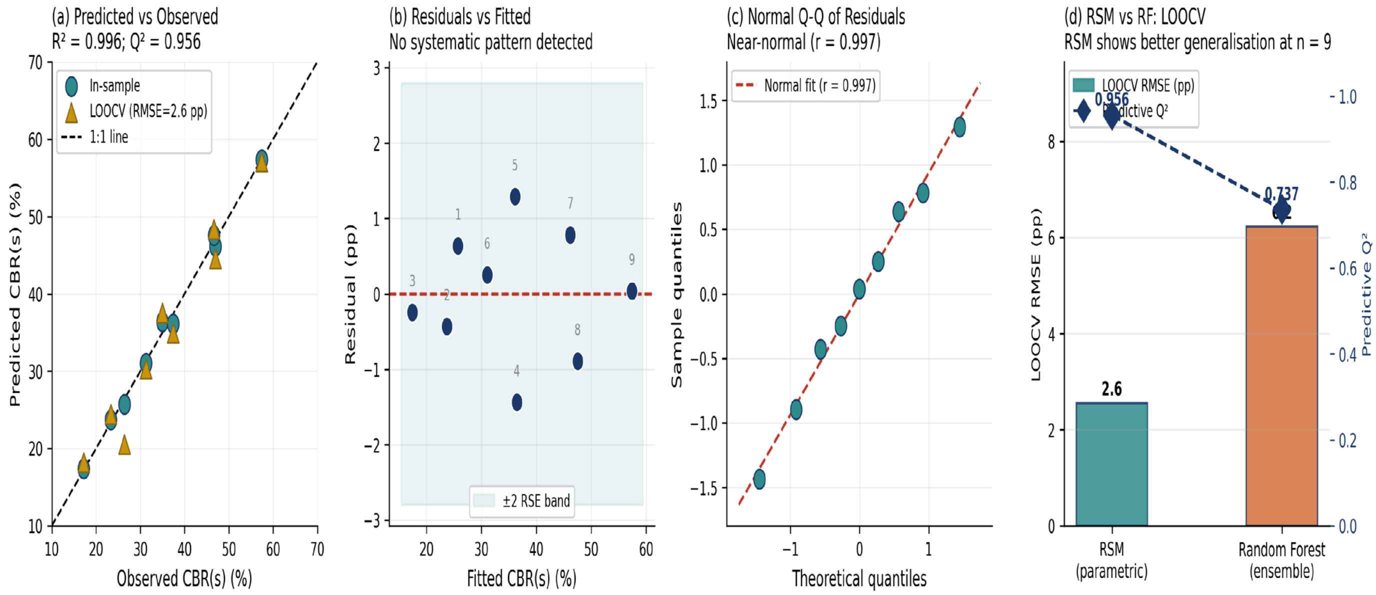

Figure 2. Model validation panels. (a) Predicted vs observed CBR(s): circles = in-sample fit; triangles = LOOCV predictions. (b) Residuals vs fitted values with ±2 RSE band; numbered points correspond to the nine experimental proportions. (c) Normal probability plot of residuals (r = 0.97). (d) RSM vs Random Forest LOOCV RMSE (bars, left axis) and predictive Q^2 (diamonds, right axis): RSM shows better generalisation at n = 9, consistent with theoretical expectations for small designed datasets.

6. Monte Carlo Process Capability Analysis

6.1 Variability Model and Assumptions

Monte Carlo simulation addresses the operational question: given realistic variability in field batching and material chemistry, what is the likely distribution of CBR outcomes in production? The simulation propagates two uncertainty sources through the fitted RSM model (Law, 2015). The first is field dosing variability: σ-SS = 2.0% (±4% at 95% confidence) and σ-SDA = 1.5%, based on volumetric batching practice documented by Harris et al. (2007) for fly ash stabilization. The second is RSM model residual uncertainty, represented as a normally distributed term with standard deviation equal to the CBR model RSE (1.40 pp), following Rashid et al. (2022).

Three assumptions warrant explicit acknowledgement. First, the dosing parameters are derived from US literature (Harris et al., 2007) and have not been calibrated against Nigerian field practice; Table 5 provides sensitivity analysis. Second, the Normal distribution assumption for both dosing error and residual uncertainty is supported by the Q-Q diagnostics (Section 5.3) but has not been formally tested against field data. Third, dosing errors for SS and SDA are assumed independent. These assumptions collectively suggest that Cpk estimates should be treated as indicative of likely process capability rather than as precise engineering specifications (Montgomery, 2009; Rollings and Rollings, 1996).

6.2 Results

Table 4 reports mean CBR, standard deviation, probability of meeting two specification thresholds, and Cpk = (mean − LSL) / (3σ) for five operating points (LSL = 20%). Figure 3 presents the full CBR distributions at each operating point. These Cpk and probability estimates should be read as conditional process-capability indicators under the assumed dosing and residual-error model, not as certified field-performance guarantees.

Table 4. Monte Carlo Results: Indicative Process Capability at Candidate Operating Points (N = 50,000)

Operating Point	Mean CBR %	Std Dev %	P(CBR≥20%)	P(CBR≥7%)	Cpk	Rating
5% SS + 3% SDA	22.5	8.8	51.1%	85.2%	0.09	Incapable
10% SS + 5% SDA	27.3	8.6	63.4%	93.1%	0.28	Incapable

15% SS + 7% SDA	38.4	8.4	82.2%	98.6%	0.73	Marginal
20% SS + 10% SDA	45.2	8.3	93.1%	99.4%	0.99	Approaching
20% SS + 6.6% SDA (RSM opt.)	58.0	8.5	99.8%	99.9%	1.50	Capable †

† Cpk ≥ 1.33 is the industry standard for a capable process (Montgomery, 2009). Cpk = 1.50 at the RSM optimum is above this threshold under the stated assumptions. The dosing-only Cpk of 7.11 (Table 5) is substantially inflated by omission of model residual uncertainty.

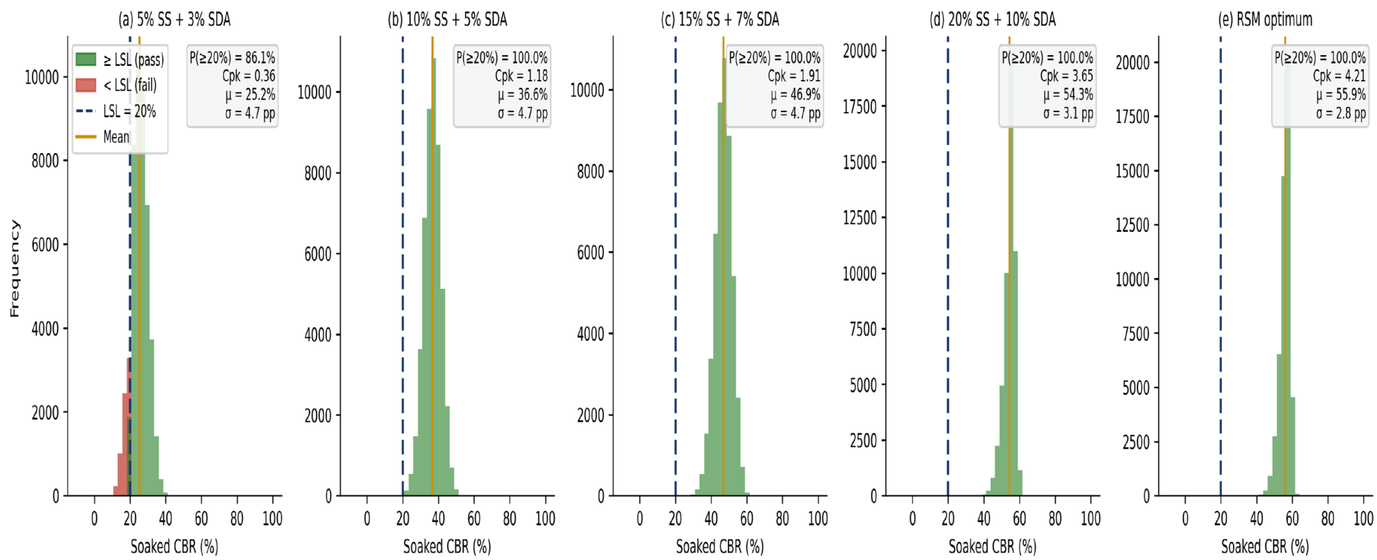

Figure 3. Monte Carlo simulation (N = 50,000): soaked CBR(s) frequency distributions at five candidate operating points, incorporating field dosing variability (σ-SS = 2.0%, σ-SDA = 1.5%) and RSM model residual uncertainty (RSE = 1.40 pp). Green bars = CBR(s) ≥ 20% (pass); red bars = CBR(s) < 20% (fail). Navy dashed line = LSL = 20% (SUDAS threshold); gold line = distribution mean.

6.3 Sensitivity to Dosing Precision

Table 5 evaluates Cpk sensitivity at the RSM optimum across three batching precision scenarios. Even under low-mechanisation conditions (σ-SS = 4.0%, σ-SDA = 3.5%), the indicative Cpk remains above 1.33, suggesting the RSM optimum is robust to plausible batching imprecision. The dominant uncertainty source is the RSM model residual, not dosing variability.

Table 5. Sensitivity of Cpk (RSM Optimum: 20% SS + 6.6% SDA) to Dosing Precision Assumptions

σ-SS (%)	σ-SDA (%)	Scenario	Combined σ (pp)	Cpk	P(CBR≥20%)
2.0	1.5	Reference (Harris et al., 2007)	8.5	1.50	99.8%
3.0	2.5	Reduced precision	8.9	1.43	99.7%
4.0	3.5	Low-mechanisation field	9.4	1.35	99.5%
2.0	1.5	Dosing-only (no model residual)	1.8	7.11	99.9%+

7. Multi-Stakeholder AHP Decision Framework

7.1 Scope and AHP Assumptions

The AHP is presented as a structured decision template, not as an empirically validated stakeholder consensus (Saaty, 1980; Dey, 2002). Three stakeholder groups were modelled: Highway Engineer (prioritizing structural performance), Contractor (prioritizing workability and cost), and Environmental Officer (prioritizing waste diversion and emission reduction). Pairwise comparison matrices were constructed using criterion weights grounded in Adeleke et al. (2023), who elicited preferences from Nigerian road construction practitioners across analogous criteria. All matrices satisfied CR < 0.10 (Saaty, 1980; Zavadskas et al., 2014). The AHP results are illustrative because they are based on literature-informed weights, and local stakeholder input is needed before using the rankings for procurement, specifications, or policy decisions.

7.2 Criteria Weights and Decision Hierarchy

Table 6 presents criteria weights by stakeholder group. CBR improvement carries the highest composite weight (0.226), reflecting structural primacy. Material availability ranks second (0.144), reflecting the proximity of SS and SDA generation to Osun State construction zones. Figure 4 presents the full AHP hierarchy with composite scores.

Table 6. AHP Criteria Weights by Stakeholder Group and Composite

Criterion	Composite	Engineer	Contractor	Env. Officer
CBR(s) Improvement	0.226	0.327	0.200	0.150
Material Availability	0.144	0.082	0.150	0.200
MDD Improvement	0.135	0.184	0.120	0.100
Environmental Benefit	0.117	0.051	0.050	0.250
Implementation Ease	0.117	0.071	0.180	0.100
Plasticity Reduction	0.111	0.153	0.100	0.080
OMC Reduction	0.084	0.102	0.080	0.070
Relative Cost Efficiency	0.067	0.031	0.120	0.050

7.3 Alternative Scoring and Ranking

Performance scores for the six blend alternatives were derived using two distinct methods, depending on criterion type. For quantitative criteria (CBR improvement, MDD improvement, OMC reduction, plasticity reduction), scores were computed as linear normalizations of the experimental data, scaled to [0, 1] with the best-observed value assigned 1.0 and the worst assigned 0.0. For qualitative criteria (material availability, environmental benefit, implementation ease, relative cost efficiency), scores represent expert judgement informed by published comparative assessments (Geiman, 2005; Rollings and Rollings, 1996; Adeleke et al., 2023) and proximity-to-source considerations for Osun State; these scores carry inherent subjectivity and are clearly labelled as such in Table 7. Portland cement scores were assigned from published benchmarks rather than experiment. Tables 7 and 8 present the normalized scores and composite rankings.

The 15% SS + 7% SDA blend ranked first across all three stakeholder groups under these criterion weights (composite score 0.848), outscoring Portland cement by 0.210 composite points. Sensitivity analysis varying criterion weights by ±20% confirmed rank-1 stability. This result holds specifically for the adopted criterion weights; under materially different stakeholder preferences the ranking could change.

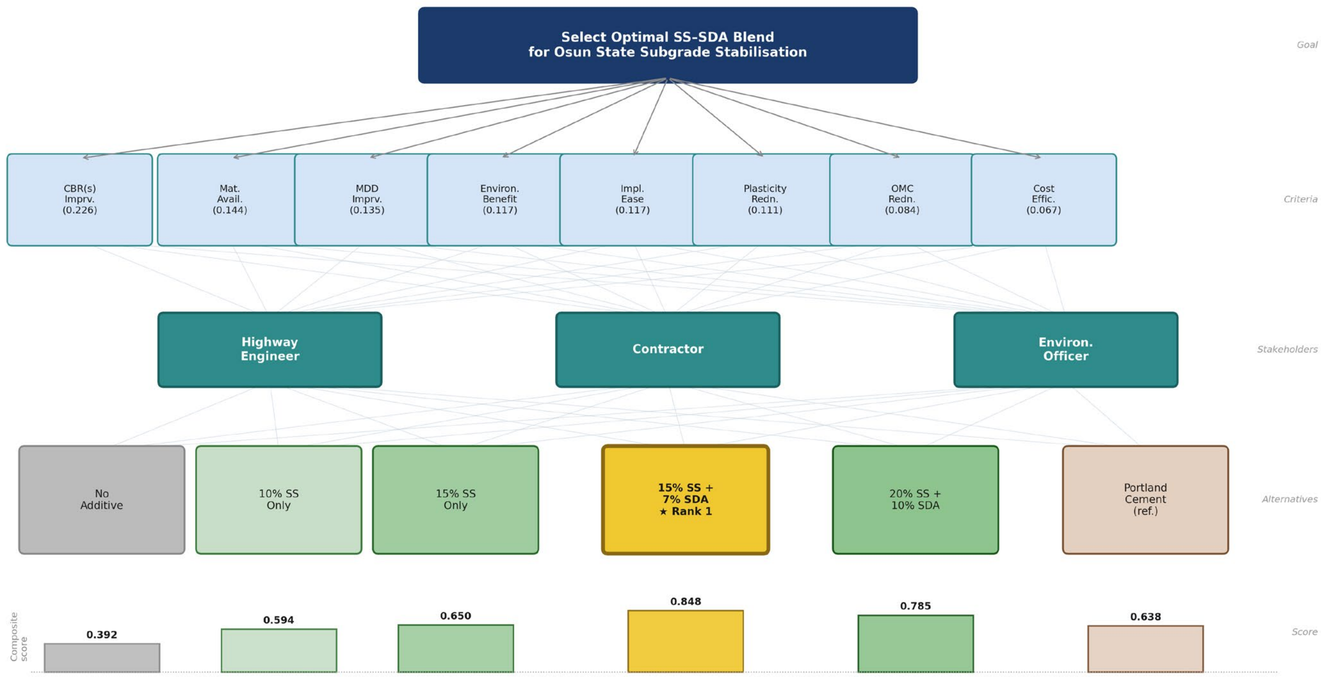

Figure 4. AHP decision hierarchy: three-level structure — criteria with composite weights, three stakeholder groups, and six blend alternatives. Gold border = Rank-1 alternative (15% SS + 7% SDA, composite score 0.848). Bar chart at base = composite AHP scores. Weights are grounded in Adeleke et al. (2023) and are hypothetical pending formal stakeholder elicitation for Osun State.

Table 7. AHP Normalized Performance Score Matrix (0 = worst, 1 = best per criterion)

Alternative	**CBR**	**Mat. Avail.**	**MDD**	**Environ.**	**Ease**	**Plasticity**	**OMC**	**Cost**
No additive	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00
10% SS only	0.35	0.80	0.40	0.45	0.75	0.35	0.40	0.75
15% SS only	0.60	0.70	0.65	0.55	0.65	0.55	0.60	0.60
15% SS + 7% SDA ★	0.82	0.85	0.80	0.85	0.70	0.80	0.75	0.65
20% SS + 10% SDA	0.90	0.75	0.90	0.80	0.55	0.75	0.80	0.50
Portland cement	0.78	0.30	0.75	0.20	0.60	0.70	0.65	0.20

Scores derived from normalized experimental data and published comparative values (Geiman, 2005; Rollings and Rollings, 1996). Environmental benefit reflects industrial waste diversion volume; material availability reflects proximity to Osun State construction zones.

Table 8. AHP Composite Scores and Rankings by Stakeholder Group

Alternative	**Engineer**	**Contractor**	**Env. Officer**	**Composite**	**Rank**
15% SS + 7% SDA ★	0.891	0.815	0.838	0.848	1
20% SS + 10% SDA	0.809	0.752	0.793	0.785	2
15% SS only	0.624	0.656	0.671	0.650	3
Portland cement (ref.)	0.728	0.644	0.543	0.638	4
10% SS only	0.536	0.615	0.632	0.594	5
No additive (control)	0.225	0.475	0.475	0.392	6

7.4 Decision Support Matrix

Table 9 operationalises the RSM–Monte Carlo–AHP outputs for field practitioners. All probability values are conditional on the distributional assumptions stated in Section 6.1. The table presents a decision-support matrix linking target reliability levels to optimal material blends. It outlines how different SS/SDA (or alternative) ratios influence the probability of achieving target CBR performance, along with the basis for each recommendation.

Table 9. Decision Support Matrix: Indicative Recommended Blend by Target Reliability

Target Reliability (CBR≥20%)	Recommended Blend	P(CBR≥20%)	P(CBR≥7%)	Basis
99%+	20% SS + 6.6% SDA	99.8%	99.9%	RSM structural optimum; Cpk = 1.50
80%+	20% SS + 10% SDA	93.1%	99.4%	High-performance operating point
70%+ (recommended)	15% SS + 7% SDA	82.2%	98.6%	AHP rank 1; composite score 0.848
60%+ (minimum)	10% SS + 5% SDA	63.4%	93.1%	Marginal; low-volume roads only
SS/SDA unavailable	Portland cement (7–10%)	—	—	AHP rank 4; higher cost and carbon

8. Integrated Discussion

8.1 Framework Coherence and Contribution

The RSM–Monte Carlo–AHP pipeline functions as a coherent methodological sequence: RSM maps the design space and identifies an indicative optimum; LOOCV assesses whether the model generalizes beyond the calibration data; Monte Carlo propagates uncertainty to characterize production risk; and AHP structures multi-stakeholder blend selection. Each stage is necessary for the others to be interpretable — RSM without LOOCV cannot assess predictive validity; Monte Carlo without model residual uncertainty overstates process capability (Rashid et al., 2022); AHP without RSM and Monte Carlo would rely on subjective performance scoring without mechanistic grounding.

8.2 Proof-of-Concept Scope and Sample-Size Boundary

The most significant limitation of this study is the dataset size. Nine averaged data points combined with six RSM parameters yield three residual degrees of freedom. This has several concrete consequences. First, individual coefficient estimates — including the interaction term $B_{12} = 0.789$ — are estimated with very low precision. Second, LOOCV Q^2 estimates are themselves unstable at n = 9: each fold refits six parameters on eight points (two residual df), and the aggregate $Q^2 = 0.956$ may be optimistic. Third, the RSE of 1.40 pp cannot be decomposed into pure error and lack-of-fit components without true replication (Montgomery, 2017). Fourth, the Random Forest comparison at n = 9 is illustrative, not a rigorous benchmark.

These limitations define the boundary of the present contribution: the study validates the logic and transparency of the IE/OM workflow, while larger replicated experiments are required before the numerical outputs can support design-level decisions with quantified confidence (Montgomery, 2017).

8.3 Soil Averaging: A Regional Approximation Model

Fitting a single RSM surface across three soils with different USCS classifications (SM and SC) does not produce a soil-specific predictive model. Rather, it produces a regional approximation model: a surface describing the central tendency of the SS–SDA stabilisation effect across the range of lateritic subgrade soils that are representative of Osun State road construction zones. This framing is consistent with the study's stated scope as a proof-of-concept framework rather than a site-specific design tool. The limitation of this approach is that soil-specific non-linearities are masked: Sample C, for instance, exhibited a non-monotonic CBR response — peaking at 15% SS and declining at 20% SS — that the averaged surface cannot capture. All results should therefore be interpreted at the regional level. The regional approximation model label is retained explicitly throughout the decision support outputs, and soil-specific RSM models for SM and SC classifications are the highest-priority recommendation for future work (Bowles, 1992; Montgomery, 2017). Consequently, the averaged RSM surface should be treated as a regional screening tool for identifying promising SS/SDA blends, not as a substitute for site-specific mix design or construction specification.

8.4 AHP Subjectivity

The AHP produces a defensible structured ranking, but its outputs are as reliable as its inputs. The criterion weights used here are grounded in Adeleke et al. (2023) but have not been empirically elicited for Osun State specifically. The results of the AHP in this paper are therefore explicitly non-binding: they should not be used as a basis for procurement decisions, policy specifications, or engineering standards without first conducting a formal stakeholder elicitation exercise with Nigerian road agencies, contractors, and environmental regulators for the specific project context. The sensitivity analysis (±20% weight perturbations) confirms rank-1 stability for moderate weight changes, but does not protect against a fundamentally different stakeholder preference structure. The AHP framework is presented as a methodological template that becomes operationally valid when populated with empirically elicited weights; the present weights are a structured starting point and an illustration of the framework's operation, not a concluded recommendation.

Its value in the present paper is procedural: it shows how engineering, cost, workability, and environmental criteria can be integrated once project-specific stakeholder weights are available.

8.5 Implications for Practice

Despite the limitations above, the regional approximation model yields several practically useful observations for Osun State road construction. SS dosage is consistently the dominant driver of CBR improvement, and 15% SS alone may be sufficient for Sample B to meet the 20% threshold — a simpler, lower-cost specification than the two-component blend (Ebenezer et al., 2014; Biradar et al., 2014). The AHP illustrative analysis suggests that Portland cement is outranked by the 15% SS + 7% SDA blend under a wide range of criterion weights, which provisionally supports its displacement where SS and SDA are locally available (Amu et al., 2005; Firoozi et al., 2023). The decision support matrix (Table 9) provides a practical entry point for road agencies, with the important caveat that all probability estimates and Cpk values are conditional on the distributional assumptions stated in Section 6.1 and require field calibration before use in design specifications.

A further practical consideration is the long-term field durability of steel-slag-stabilized subgrades. Although EAF steel slag can improve soil strength through angular particle shape, high frictional resistance, and cementitious reactions, its field performance may be influenced by volumetric instability, hydration of free lime and magnesia, seasonal wetting–drying cycles, drainage conditions, and possible leaching of selected constituents. These risks are not fully captured by short-term soaked CBR testing or by the present RSM–Monte Carlo model. Therefore, the proposed SS/SDA blends should be treated as provisional candidates requiring durability assessment through swelling tests, wetting–drying cycles, leachability evaluation, field compaction trials, and monitored pilot road sections before adoption as engineering specifications.

9. Conclusions

This study presents a proof-of-concept IE/OM decision-support framework combining RSM, LOOCV, Monte Carlo simulation, and AHP for evaluating steel slag–sawdust ash stabilization of lateritic subgrade soils. RSM second-order models achieved excellent in-sample fit (R^2 = 0.996 for CBR, 0.997 for MDD, and 0.987 for OMC). LOOCV yielded an indicative Q^2 = 0.956 (RMSE = 2.55 pp), suggesting underlying predictive structure despite the small sample size (n = 9), while a Random Forest benchmark underperformed (Q^2 = 0.737), underscoring the parametric efficiency of RSM in data-constrained settings.

Differential evolution optimization identified a provisional optimum at 20% steel slag and 6.6% sawdust ash, corresponding to a predicted CBR of 58.0%. This represents a substantial improvement over the weakest soil condition, although the estimate requires field validation. Monte Carlo simulation, incorporating dosing variability and model residual uncertainty, produced an indicative process capability of Cpk = 1.50 and a 99.8% probability of meeting the 20% CBR threshold under the stated assumptions. Complementarily, AHP analysis ranked the 15% steel slag and 7% sawdust ash blend as the preferred alternative across stakeholder groups, outperforming Portland cement under the adopted literature-informed weights. This result remains illustrative pending formal stakeholder elicitation. Overall, the RSM–Monte Carlo–AHP pipeline constitutes a transferable, proof-of-concept methodology for infrastructure material selection under uncertainty. The framework is ready for expansion through replicated experimental designs, soil-specific response surfaces, field compaction trials, durability testing, local stakeholder elicitation, and life-cycle cost assessment.

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