Innovations

Evaluation of Bricks Under Eco-Friendly Perspective through MCDM Framework

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Abstract: *This research focuses on developing Fly Ash, Clay, and Carbon Black (FCCB) bricks as a sustainable construction material, aiming to reduce raw material consumption, energy use, and environmental emissions while maintaining sufficient structural and thermal performance. A robust multi-criteria decision-making (MCDM) framework is proposed, integrating CRITIC (Criteria Importance Through Intercriteria Correlation) and CODAS (Combinative Distance-based Assessment) methodologies to evaluate and rank FCCB brick formulations. The CRITIC method objectively determines criteria weights by analyzing variability and interdependencies, while CODAS ranks alternatives using Euclidean and Taxicab distances from the negative-ideal solution. This empirical approach, utilizing data from documented studies, industry records, and reported performance metrics, to reflect realistic material behavior and sustainability outcomes. Twenty-seven FCCB mix proportions, comprising clay, fly ash, carbon black, and cement, are assessed across seven criteria: raw material cost, water and fuel depletion, energy requirements, cement and sand demand, global warming potential (GWP), acidification potential (AP), cultural acceptance, skilled labor requirements, thermal conductivity, compressive strength, water absorption, and bulk density. This methodology ensures transparent, consistent, and data-driven prioritization of sustainable brick alternatives, providing actionable insights for material scientists, construction engineers, and policymakers to promote environmentally responsible construction practices.*

Keywords: *Cement, Fly Ash, Clay, Carbon Black, FCCB, Taguchi*, *CRITIC, CODAS*

1. Introduction

Contemporary engineering and product development necessitate advanced methodologies to address the complexities of multi-objective optimization, where multiple, often conflicting, performance criteria must be balanced. Traditional single-objective optimization approaches, which prioritize a solitary performance metric, are inadequate for modern challenges that demand simultaneous improvement across diverse attributes. Such trade-offs, where enhancement of one criterion may compromise another, underscore the limitations of conventional methods and highlight the need for robust multi-objective decision-making frameworks. This study proposes an integrated methodology combining the Taguchi method, CRITIC (Criteria Importance Through Intercriteria Correlation), and CODAS (Combinative Distance-based Assessment) to provide a systematic, transparent, and objective approach to optimization. The Taguchi method facilitates efficient experimental design, CRITIC assigns objective weights to criteria based on their variability and interdependencies, and CODAS ranks alternatives by measuring their proximity to ideal solutions, ensuring reliable and reproducible results.

The construction industry, a major global consumer of natural resources and energy, significantly contributes to greenhouse gas (GHG) emissions. Fired clay bricks, widely used in developing nations due to their cost-effectiveness and availability, rely on energy-intensive kiln firing and consume fertile topsoil, leading to resource depletion, ecological degradation, and air pollution (UNEP, 2014). Fly ash-based bricks have emerged as a sustainable alternative, offering reduced embodied energy, lower water consumption, and enhanced thermal insulation properties (IS 12894, 2002; BIS, 2016). Research indicates that higher fly ash content decreases bulk density and thermal conductivity, improving building energy efficiency (Naik & Kraus, 2003), while maintaining compressive strengths that meet or exceed IS 3495 standards (Singh & Garg, 1993). Concurrently, industrial by-products such as fly ash from thermal power plants and carbon black from pyrolysis processes pose significant disposal challenges. Repurposing these materials into Fly Ash–Clay–Carbon Black (FCCB) bricks present a viable strategy to advance circular economy principles, reducing raw material costs, environmental impacts, and landfill waste.

Despite their potential, optimizing FCCB brick compositions remains complex due to the interplay of conflicting criteria, including mechanical strength, durability, thermal conductivity, cost, energy and water demand, emissions, and socio-cultural acceptance. For example, increased cement content enhances strength but elevates costs and carbon emissions (Hammond & Jones, 2011), while higher fly ash proportions reduce environmental impact and cost but may encounter cultural resistance (Kumar et al., 2001; Pappu et al., 2007). These trade-offs necessitate a multi-criteria decision-making (MCDM) framework that integrates technical, economic, environmental, and social considerations. The CRITIC method (Diakoulaki et al., 1995) mitigates subjectivity by objectively weighting criteria based on their variability and intercorrelations, while CODAS (Ghorabaee et al., 2016) provides robust ranking of alternatives through Euclidean and Taxicab distance metrics. Hybrid CRITIC–CODAS frameworks have proven effective in sustainable material selection (Pramanik & Sarkar, 2020), with empirical data from standards, industry records, and prior studies enhancing evaluation reliability beyond experimental trials (Triantaphyllou, 2000). Although recent studies emphasize the multi-dimensional nature of brick sustainability assessment (Saurabh et al., 2018; Tiwari et al., 2024; Maaze, 2025), comprehensive analyzes of FCCB compositions remain scarce.

To address this gap, this research employs an integrated Taguchi–CRITIC–CODAS framework to systematically evaluate FCCB bricks. The research objectives are to: (1) assess the impact of clay, fly ash, carbon black, cement, gypsum, stone dust, and polycarboxylate ether on sustainability performance; (2) determine objective criteria weights using the CRITIC method; (3) formulate 27 FCCB brick compositions via a Taguchi L27 orthogonal array and rank them for sustainability using CODAS; and (4) elucidate trade-offs among performance, cost, and environmental efficiency. The findings aim to provide actionable insights for material scientists, construction engineers, and policymakers to advance sustainable construction practices and promote eco-efficient technologies.

2. Criteria for Evaluation of Sustainability

To determine the sustainability index of a brick mix, each constituent material is classified as either a benefit-type or cost-type criterion based on its environmental impact and role in promoting sustainable practices.

2.1 Nature of Factors from a Sustainability Perspective

2.1.1 CB_% (Carbon Black) → Benefit

Carbon black is classified as a benefit-type factor when sourced sustainably, such as through pyrolysis of end-of-life tires to produce recovered carbon black (rCB). This process diverts non-biodegradable tire waste from landfills and illegal dumping, reducing environmental harm. Using rCB decreases reliance on virgin petroleum-based carbon black, which is energy-intensive and emits significant CO_2 during production. Each ton of rCB replaces an equivalent amount of virgin carbon black, reducing embodied CO_2 and fossil resource consumption. When incorporated into bricks, rCB supports circular economy principles by closing the loop between waste generation and material reuse. Provided recovery processes minimize toxic emissions, higher proportions of sustainably sourced carbon black enhance the sustainability performance of the brick mix.

2.1.2 FA_% (Fly Ash) → Benefit

Fly ash, a by-product of coal-fired power plants, is a benefit-type factor. Its use in construction diverts industrial waste from landfills, mitigates disposal challenges, reduces embodied CO_2 by partially replacing cement, and conserves virgin raw materials. Higher fly ash content directly improves the sustainability of the brick mix.

2.1.3 CE_% (Cement) → Cost

Cement has a high carbon intensity (approximately 0.8–0.9 t CO_2/ton) due to its energy-intensive production process, which requires high temperatures and significant fuel consumption. As the largest contributor to embodied CO_2 in a brick mix, cement is classified as a cost-type factor.

2.1.4 CL_% (Clay) → Cost

Excessive clay extraction depletes topsoil and disrupts ecological balance. However, partial replacement with sustainable alternatives like fly ash or carbon black reduces environmental impact. Due to its potential for ecological harm, clay is classified as a cost-type factor.

2.1.5 GY_% (Gypsum) → Benefit

Recycled gypsum reduces the need for cement, enhances setting properties, and promotes resource circularity by minimizing waste. Its use in brick production supports sustainable practices, making it a benefit-type factor.

2.1.6 SA_% (Stone Dust) → Benefit

Stone dust, a by-product of quarrying, promotes waste utilization, conserves natural resources, enhances energy efficiency, and improves brick performance. Its incorporation into brick mixes supports sustainability, classifying it as a benefit-type factor.

2.1.7 PCE_% (Polycarboxylate Ether – Superplasticizer) → Cost

Polycarboxylate ether (PCE)-based superplasticizers are petrochemical derivatives, and their production involves energy-intensive processes and synthetic chemicals, contributing to embodied emissions. Although PCE improves workability and indirectly reduces cement demand, its environmental footprint outweighs these benefits. Therefore, PCE is classified as a cost-type factor.

2. Methodology for Empirical Evaluation of FCCB Bricks

The sustainability of Fly Ash, Clay, and Carbon Black (FCCB) bricks was evaluated using the Combinative Distance-based Assessment (CODAS) method within an integrated Multi-Criteria Decision-Making (MCDM) framework. The methodology was implemented in Python, following a systematic sequence of steps to rank FCCB brick alternatives based on their sustainability performance. The evaluation criteria include material-specific sustainability factors, classified as benefit-type or cost-type, as described in Section 2.1. The detailed computational procedure is outlined below.

Step 1.Construction of the Decision Matrix:

A decision matrix X= $[x_{ij}]$was developed, with rows representing FCCB brick alternatives (i=1, 2., m) and columns representing evaluation criteria (j=1, 2,….,n). Each element x_{ij} indicates the performance score of alternatives i for criterion j, based on empirical data.

Step 2. Normalization of the Decision Matrix: To ensure comparability across criteria with different units, min-max normalization was applied. For a benefit-type criterion, the normalized score $z_{ij}$is computed as:

$$z_{ij} = \frac{x_{ij} - min(x_j)}{max(x_j) - min(x_j)} \quad \text{for benefit criteria}$$

$$z_{ij} = \frac{max(x_j) - x_{ij}}{max(x_j) - min(x_j)} \quad \text{for cost criteria}$$

Here, x_{ij}denoted the performance of alternative i under criterion j.

If the dispersion of a criterion was zero (Max_j = Min_j), the normalized score was set to 1

Step 3: Weight Determination: Criteria weights are determined from Objective weighting

techniques (CRITIC) method. The following steps are required for fining out the weight

determination.

(i) Standard deviation of each criterion: For each normalized criterion j, compute the standard deviation from the following relation

$$\sigma_j = \sqrt{\frac{1}{m}\sum_{i=1}^{m} (z_{ij} - \overline{z}_j)^2}$$

Here $\sigma_j$reflects the contrast intensity (information content) of criterionj.

A higher σ_j means greater discrimination ability across alternatives.

(ii) Correlation matrix: Compute the Pearson correlation coefficient (r_{jk}) between each pair of criteria j and k from the following relation.

$$r_{jk} = \frac{\sum_{i=1}^{m} (z_{ij} - \overline{z}_j)\,(z_{ik} - \overline{z}_k)}{\sqrt{\sum_{i=1}^{m} (z_{ij} - \overline{z}_j)^2}\sqrt{\sum_{i=1}^{m} (z_{ik} - \overline{z}_k)^2}}$$

z_{ij} = value of the i^{th} observation of variable j

z_{ik}= value of the i^{th} observation of variable k

$\bar{z}_j$ = mean of variable j

$\bar{z}_k$ = mean of variable k

So z_{ik}represents the observed data values of the k^{th} variable.

(iii)Information content of each criterion: Compute the amount of information carried by criterion j:

$$C_j = \sigma_j \cdot \sum_{k=1}^{n} (1 - r_{jk})$$

σ_j = Constant intensity (Variability),

$(1 - r_{jk})$ = Degree of conflict with criterion k.

Thus, C_j combines dispersion and conflict of each criterion

(iv) Determination of weights: Normalize the information content values into final weights:

$$w_j = \frac{C_j}{\sum_{j=1}^{n} C_j}$$

$w_j \rightarrow$ the weight (or normalized value) of the j^{th} component.

$C_j \rightarrow$ the value, score, or contribution of the j^{th} component.

Step 4: Construction of Weighted Normalized Matrix: The weighted normalized decision matrix was computed as:

$$V_{ij} = w_j \cdot z_{ij}$$

$V_{ij} \rightarrow$ The weighted normalized value for the i^{th} alternative (or observation) with respect to the j^{th} criterion (or material).

$w_j \rightarrow$ The weight (importance, proportion, or contribution factor) of criterion j.

$z_{ij} \rightarrow$ The normalized score or value of the i^{th} alternative for criterion j.

Step 5: Determination of Negative-Ideal Solution (NIS): The Negative-Ideal Solution (NIS) vector was obtained by selecting the minimum value of each criterion across alternatives:

$$v_j^- = \min_i V_{ij}$$

$v_j^- \rightarrow$ This represents the negative-ideal solution (or the worst value) for criterion j.

$V_{ij} \rightarrow$ The weighted normalized value of alternative iii with respect to criterion j.

$\min_i \rightarrow$ Means we take the minimum value of V_{ij} across all alternatives i.

Step 6: Distance Measures: For each alternative i, distances from the NIS were computed using two metrics:

Euclidean Distance:

$$S_i^- = \sqrt{\sum_{j=1}^{n} (V_{ij} - v_j^-)^2}$$

- S_i^- = distance of alternative i from the NIS
- V_{ij} = weighted normalized value of alternative iii for criterion j
- v_j^- = minimum (worst) value of criterion j across all alternatives
- This gives the geometric distance in multi-dimensional space.

Taxicab (Manhattan)

$$D_i^- = \sum_{j=1}^{n} |V_{ij} - v_j^-|$$

D_i^- = distance of alternative i from the NIS

Step 7: CODAS Assessment Score: The final CODAS assessment score (Hi) for each alternative was derived as:

$$H_i = E_i + \tau \cdot T_i$$

- H_i → The final CODAS score for alternative i.
- E_i → Euclidean distance of alternative i from the Negative Ideal Solution (NIS).
- T_i → Taxicab (Manhattan) distance of alternative i from the NIS.
- τ → A small threshold parameter (default 0.02) that controls how much the Taxicab distance contributes to the final score.

Step 8: Ranking of Alternatives:
Alternatives were ranked in descending order of their CODAS scores Hi. A higher Hi indicates greater sustainability and suitability of the FCCB brick alternative. In case of ties, the Taxicab distance Ti was used as a tiebreaker to ensure a unique ranking.

4. **Illustration of the Taguchi Methodology:**
In the domain of multi-objective optimization, the Taguchi method transcends its conventional application as an independent optimization technique. Instead, its primary value lies in functioning as a robust data generation mechanism. This capability is essential for supplying the requisite decision matrix to subsequent multi-criteria decision-making (MCDM) frameworks, such as the integrated CRITIC-CODAS approach. Relying on conventional exhaustive experimentation to construct this matrix would incur substantial temporal and financial burdens, especially in scenarios characterized by high-dimensional factor spaces. By contrast, the Taguchi method—rooted in orthogonal array designs—facilitates the efficient derivation of a comprehensive dataset that captures diverse experimental configurations through a parsimonious set of trials. This method systematically elucidates the interdependencies between controllable parameters and multiple performance metrics, thereby establishing a foundational empirical basis that renders the ensuing multi-objective evaluation both viable and computationally tractable.

The proposed methodology is illustrated in the following:

4.1 Generation of alternate bricks:

The Taguchi L27 orthogonal array (OA) design is employed to optimize the production of alternative bricks by systematically evaluating multiple control factors. The array comprises 27 experimental runs, represented as rows in the design matrix. The L27 design accommodates up to seven factors, each evaluated at three distinct levels (e.g., low, medium, high).

Without the use of an orthogonal array, a full factorial design for seven factors at three levels would necessitate 2,187experimental trials to capture all possible combinations. By leveraging the L27 orthogonal array, the Taguchi method reduces the required experimental runs to just 27, while still effectively capturing the main effects and key interactions of the factors.

This significant reduction in the number of trials—from 2,187 to 27—substantially lowers the experimental cost and time, making the Taguchi L27 design a highly efficient tool for optimizing brick production processes.

This methodology ensures a robust and resource-efficient approach to identifying optimal parameter settings for alternative brick manufacturing, facilitating practical implementation in multi-objective optimization studies.

4.2 Initial Decision Matrix: Initial decision matrix is developed based on the Taguchi L 27 design by considering the actual levels of the factors.The initial decision matrix generated from the Taguchi L27 design is presented in Table 1.

Table 1: Initial decision Matrix

Run	FA	CB	CLAY	CEMENT	GYPSUM	STONE DUST	PCE
1	50	50	35	8	1.5	20	0.5
2	50	50	35	8	1.75	27.5	0.575
3	50	50	35	8	2	25	0.65
4	50	60	40	10	1.5	20	0.5
5	50	60	40	10	1.75	27.5	0.575
6	50	60	40	10	2	25	0.65
7	50	70	45	12	1.5	20	0.5
8	50	70	45	12	1.75	27.5	0.575
9	50	70	45	12	2	25	0.65
10	60	50	40	12	1.5	27.5	0.65
11	60	50	40	12	1.75	25	0.5
12	60	50	40	12	2	20	0.575
13	60	60	45	8	1.5	27.5	0.65
14	60	60	45	8	1.75	25	0.5

15	60	60	45	8	2	20	0.575
16	60	70	35	10	1.5	27.5	0.65
17	60	70	35	10	1.75	25	0.5
18	60	70	35	10	2	20	0.575
19	70	50	45	10	1.5	25	0.575
20	70	50	45	10	1.75	20	0.65
21	70	50	45	10	2	27.5	0.5
22	70	60	35	12	1.5	25	0.575
23	70	60	35	12	1.75	20	0.65
24	70	60	35	12	2	27.5	0.5
25	70	70	40	8	1.5	25	0.575
26	70	70	40	8	1.75	20	0.65
27	70	70	40	8	2	27.5	0.5

4.3 Actual decision matrix:

In experimental design and material composition analysis, normalization or percentage scaling is a critical process to ensure that the proportions of different constituents sum to 100%. This is particularly relevant when designing mixtures or analysing material compositions where the total contribution of all components must equal 100%. The normalization process involves the computation of scaling factor and the normalization of Factor Percentages.

The scaling factor is calculated using the formula:(K=100/Sum of % values of all the factors) Here, the sum of the percentage values of all factors represents the total unnormalized contribution of the constituents.

In the Normalization of Factor Percentages,each factor's percentage in a given experimental run is multiplied by the scaling factor K to obtain the normalized percentage. This ensures that the adjusted proportions collectively sum to 100%, forming the actual decision matrix used for further analysis.

This normalization process ensures a consistent and accurate representation of constituent proportions, facilitating reliable comparisons and evaluations in multi-objective optimization studies, such as those involving material compositions or mixture designs.The normalized percentage values for constituent materials are summarized in Table 2.

Table 2: Decision matrix

Run	FA	CB	CLAY	CEMENT	GYPSUM	STONE DUST	PCE
1	30.30	30.30	21.21	4.85	0.91	12.12	0.30
2	28.93	28.93	20.25	4.63	1.01	15.91	0.33
3	29.30	29.30	20.51	4.69	1.17	14.65	0.38
4	27.47	32.97	21.98	5.49	0.82	10.99	0.27
5	26.34	31.61	21.07	5.27	0.92	14.49	0.30

6	26.65	31.97	21.32	5.33	1.07	13.32	0.35
7	25.13	35.18	22.61	6.03	0.75	10.05	0.25
8	24.18	33.85	21.76	5.80	0.85	13.30	0.28
9	24.43	34.20	21.99	5.86	0.98	12.22	0.32
10	31.31	26.09	20.87	6.26	0.78	14.35	0.34
11	31.70	26.42	21.14	6.34	0.92	13.21	0.26
12	32.51	27.09	21.67	6.50	1.08	10.84	0.31
13	29.61	29.61	22.21	3.95	0.74	13.57	0.32
14	29.96	29.96	22.47	4.00	0.87	12.48	0.25
15	30.68	30.68	23.01	4.09	1.02	10.23	0.29
16	29.32	34.20	17.10	4.89	0.73	13.44	0.32
17	29.67	34.61	17.31	4.94	0.87	12.36	0.25
18	30.37	35.43	17.71	5.06	1.01	10.12	0.29
19	34.64	24.74	22.27	4.95	0.74	12.37	0.28
20	35.46	25.33	22.80	5.07	0.89	10.13	0.33
21	34.15	24.39	21.95	4.88	0.98	13.41	0.24
22	34.30	29.40	17.15	5.88	0.74	12.25	0.28
23	35.11	30.09	17.55	6.02	0.88	10.03	0.33
24	33.82	28.99	16.91	5.80	0.97	13.29	0.24
25	32.55	32.55	18.60	3.72	0.70	11.62	0.27
26	33.27	33.27	19.01	3.80	0.83	9.51	0.31
27	32.11	32.11	18.35	3.67	0.92	12.61	0.23

4.4 **Normalized Decision matrix:** Normalized matrix is determined as discussed in step 2 of section 3. Normalized decision matrix is presented in table 3.

Table 3: Normalized Decision Matrix

Alt	**FA**	**CB**	**CLAY**	**CEMENT**	**GYPSUM**	**STONE DUST**	**PCE**
A1	0.5430	0.5356	0.2945	0.5837	0.4460	0.4083	0.4862
A2	0.4214	0.4113	0.4520	0.6613	0.6641	1.0000	0.6820
A3	0.4541	0.4447	0.4097	0.6404	1.0000	0.8030	1.0000
A4	0.2922	0.7769	0.1690	0.3556	0.2671	0.2315	0.2994
A5	0.1918	0.6538	0.3175	0.4356	0.4730	0.7776	0.4854
A6	0.2189	0.6870	0.2775	0.4140	0.7763	0.5958	0.7723
A7	0.0842	0.9770	0.0649	0.1664	0.1187	0.0850	0.1445
A8	0.0000	0.8565	0.2051	0.2470	0.3133	0.5917	0.3211
A9	0.0228	0.8890	0.1672	0.2252	0.5897	0.4231	0.5824
A10	0.6319	0.1539	0.3504	0.0848	0.1796	0.7560	0.7246
A11	0.6671	0.1839	0.3070	0.0567	0.4789	0.5782	0.2299
A12	0.7383	0.2445	0.2193	0.0000	0.8137	0.2076	0.5422
A13	0.4814	0.4726	0.1317	0.9018	0.0901	0.6344	0.6031

A14	0.5128	0.5048	0.0880	0.8851	0.3719	0.4650	0.1342
A15	0.5763	0.5696	0.0000	0.8514	0.6853	0.1125	0.4266
A16	0.4557	0.8890	0.9682	0.5703	0.0749	0.6137	0.5824
A17	0.4866	0.9258	0.9349	0.5499	0.3537	0.4457	0.1179
A18	0.5488	1.0000	0.8678	0.5085	0.6634	0.0963	0.4070
A19	0.9273	0.0320	0.1213	0.5484	0.0945	0.4474	0.3642
A20	1.0000	0.0851	0.0349	0.5070	0.3985	0.0977	0.6594
A21	0.8835	0.0000	0.1734	0.5733	0.5862	0.6102	0.0960
A22	0.8972	0.4539	0.9603	0.2194	0.0792	0.4284	0.3458
A23	0.9685	0.5163	0.8944	0.1707	0.3797	0.0819	0.6376
A24	0.8543	0.4163	1.0000	0.2487	0.5663	0.5899	0.0804
A25	0.7418	0.7389	0.7230	0.9824	0.0000	0.3306	0.2507
A26	0.8059	0.8044	0.6553	0.9532	0.2830	0.0000	0.5251
A27	0.7031	0.6993	0.7639	1.0000	0.4636	0.4853	0.0000

4.5 **Determination of Relative weights:** Relative weights of the factors are determined by developing the python code for CRITIC method as discussed in step 3.Standard deviation, Correlation matrix and relative weights of the criteria are presented below. The standard deviation values of criteria are shown in Table 4, the correlation coefficients among criteria in Table 5, and the final relative weights of the evaluation criteria in Table 6.

Table 4: Standard Deviation of Criteria:

Factor	FA	CB	CLAY	CEMENT	GYPSUM	STONE DUST	PCE
std_dev	0.2889	0.2969	0.3372	0.3001	0.2580	0.2594	0.2473

Table 5; Correlation matrix:

Criteria	FA	CB	CLAY	CEMENT	GYPSUM	STONE DUST	PCE
FA	1.0000	-0.6249	0.3182	0.1293	-0.1142	-0.2591	-0.1102
CB	-0.6249	1.0000	0.3228	0.1581	-0.1161	-0.2543	-0.1282
CLAY	0.3182	0.3228	1.0000	0.0319	-0.1385	0.0067	-0.1446
CEMENT	0.1293	0.1581	0.0319	1.0000	-0.0943	-0.0056	-0.0986
GYPSUM	-0.1142	-0.1161	-0.1385	-0.0943	1.0000	0.1528	0.3107
SANDDUST	-0.2591	-0.2543	0.0067	-0.0056	0.1528	1.0000	0.1942
PCE	-	-	-	-0.0986	0.3107	0.1942	1.0000

	0.1102	0.1282	0.1446				

Table 6: Weights of the Criteria:

Criteria	FA	CB	CLAY	CEMENT	GYPSUM	STONE DUST	PCE
Rel. Wt	0.1581	0.1620	0.1552	0.1449	0.1271	0.1313	0.1214

4.6 Determine Weighted Normalized Matrix: Weighted normalized decision matrix is determined as discussed in step 4 of the methodology section and is shown in table 7.

Table 7: Weighted Normalized matrix:

Alts	FA	CB	CLAY	CEMENT	GYPSUM	STONE DUST	PCE
A1	0.0858	0.0868	0.0457	0.0846	0.0567	0.0536	0.0590
A2	0.0666	0.0666	0.0701	0.0958	0.0844	0.1313	0.0828
A3	0.0718	0.0720	0.0636	0.0928	0.1271	0.1054	0.1214
A4	0.0462	0.1259	0.0262	0.0515	0.0339	0.0304	0.0363
A5	0.0303	0.1059	0.0493	0.0631	0.0601	0.1021	0.0589
A6	0.0346	0.1113	0.0431	0.0600	0.0987	0.0782	0.0938
A7	0.0133	0.1583	0.0101	0.0241	0.0151	0.0112	0.0175
A8	0.0000	0.1387	0.0318	0.0358	0.0398	0.0777	0.0390
A9	0.0036	0.1440	0.0260	0.0326	0.0750	0.0555	0.0707
A10	0.0999	0.0249	0.0544	0.0123	0.0228	0.0993	0.0880
A11	0.1055	0.0298	0.0476	0.0082	0.0609	0.0759	0.0279
A12	0.1167	0.0396	0.0340	0.0000	0.1034	0.0273	0.0658
A13	0.0761	0.0766	0.0204	0.1307	0.0115	0.0833	0.0732
A14	0.0811	0.0818	0.0137	0.1283	0.0473	0.0610	0.0163
A15	0.0911	0.0923	0.0000	0.1234	0.0871	0.0148	0.0518
A16	0.0721	0.1440	0.1503	0.0826	0.0095	0.0806	0.0707
A17	0.0769	0.1500	0.1451	0.0797	0.0450	0.0585	0.0143
A18	0.0868	0.1620	0.1347	0.0737	0.0843	0.0126	0.0494
A19	0.1466	0.0052	0.0188	0.0795	0.0120	0.0587	0.0442
A20	0.1581	0.0138	0.0054	0.0735	0.0506	0.0128	0.0800
A21	0.1397	0.0000	0.0269	0.0831	0.0745	0.0801	0.0117
A22	0.1419	0.0735	0.1490	0.0318	0.0101	0.0563	0.0420
A23	0.1531	0.0836	0.1388	0.0247	0.0483	0.0107	0.0774
A24	0.1351	0.0674	0.1552	0.0360	0.0720	0.0775	0.0098
A25	0.1173	0.1197	0.1122	0.1423	0.0000	0.0434	0.0304
A26	0.1274	0.1303	0.1017	0.1381	0.0360	0.0000	0.0638
A27	0.1112	0.1133	0.1186	0.1449	0.0589	0.0637	0.0000

4.7 Determine the Negative-Ideal Solution (NIS).

In multi-criteria decision-making (MCDM), the Negative Ideal Solution (NIS) is defined as a vector comprising the minimum weighted normalized performance values for each criterion. It encapsulates a hypothetical scenario representing the worst possible performance across all evaluated criteria. The NIS is typically assigned a value of zero, serving as a baseline reference for assessing alternatives in the decision-making process.

4.8 Determine Euclidean and Taxicab distance measures and Ranking:

In the Combinative Distance-based Assessment (CODAS) method, the Euclidean and taxicab (Manhattan) distance measures are computed as outlined in Step 6 of the methodology. These distances quantify the separation between each alternative and both the Positive Ideal Solution (PIS) and Negative Ideal Solution (NIS). Specifically, the Euclidean distance reflects the straight-line (L2-norm) separation, while the taxicab distance captures the L1-norm path along the axes, providing complementary insights into alternative performance. Subsequently, the assessment score for each alternative is derived as detailed in Step 7, integrating these distances to yield a comprehensive ranking. The resulting Euclidean and taxicab distance measures, along with the final ranking of alternatives, are summarized in Table 8.

Table 8: Euclidean and Taxicab distance measures and Ranking:

Alts	**Euclidean**	**Taxicab**	**H_i**	**Rank**
A1	0.1836	0.4722	0.1931	20
A2	0.2328	0.5977	0.2448	10
A3	0.2550	0.6541	0.2680	5
A4	0.1572	0.3505	0.1642	26
A5	0.1899	0.4698	0.1993	17
A6	0.2090	0.5196	0.2194	12
A7	0.1630	0.2496	0.1680	25
A8	0.1752	0.3629	0.1824	24
A9	0.1903	0.4074	0.1984	19
A10	0.1784	0.4016	0.1864	23
A11	0.1568	0.3558	0.1640	27
A12	0.1792	0.3869	0.1870	22
A13	0.2039	0.4718	0.2133	14
A14	0.1901	0.4294	0.1986	18
A15	0.2062	0.4604	0.2154	13
A16	0.2587	0.6098	0.2709	4
A17	0.2479	0.5695	0.2593	7
A18	0.2589	0.6035	0.2710	3
A19	0.1837	0.3650	0.1910	21
A20	0.1994	0.3943	0.2073	15
A21	0.1981	0.4159	0.2064	16
A22	0.2319	0.5045	0.2420	11
A23	0.2424	0.5367	0.2531	9
A24	0.2438	0.5529	0.2549	8

A25	0.2525	0.5654	0.2638	6
A26	0.2607	0.5973	0.2727	1
A27	0.2603	0.6105	0.2725	2

5 Results and Discussion

In this study, the CODAS composite score (Hi) is adopted as the Sustainability Index (SI) for evaluating alternative brick compositions. To facilitate meaningful comparisons, min–max normalization is applied to scale the Hi values within the range of [0, 1]. The results reveal a clear hierarchy among the alternatives, with distinct performance tiers. Alternatives A26, A27, and A18 achieved the highest sustainability indices (SI ≥ 0.98), establishing them as the most sustainable options, closely followed by A16 and A3. A group of mid-tier alternatives, including A2, A22, A6, A15, and A13, exhibited moderate sustainability performance, suggesting potential for enhancement through targeted optimization of composition parameters, such as increasing the proportions of fly ash, gypsum, or stone dust while reducing cement or clay content. Conversely, alternatives A11, A4, and A7 recorded the lowest sustainability indices (SI ≤ 0.04), indicating poor sustainability under their current mix designs. These findings provide actionable insights for decision-makers, supporting the adoption and scale-up of top-ranked alternatives, the refinement of mid-tier formulations, and the reengineering or replacement of the least sustainable options. By leveraging CODAS composite scores as a sustainability index, this study offers a transparent and rational framework for ranking, selecting, and advancing eco-friendly brick compositions.

Concluding Remarks

In this study, the Criteria Importance Through Intercriteria Correlation (CRITIC) method was employed to determine objective weights for the evaluation criteria, effectively capturing both the variability within the data and the interdependencies among criteria. These weights were subsequently integrated into the Combinative Distance-based Assessment method (CODAS), which utilized Euclidean and Taxicab distance measures to generate a robust ranking of brick alternatives. This approach was designed to address the shortcomings of subjective or single-criterion selection methods, establishing a structured and scientifically grounded framework for evaluating sustainable construction materials. The findings demonstrate the efficacy of combining CRITIC and CODAS, offering a reliable decision-making tool that provides a transparent basis for manufacturers and policymakers to optimize material compositions and promote eco-friendly alternatives in the construction industry.

A key feature of this study is the treatment of the CODAS-derived composite score as the Sustainability Index (SI), which serves as a critical response variable alongside engineering properties such as compressive strength and durability indicators. This integrated approach ensures that the selection of optimal brick formulations balances mechanical performance with environmental responsibility, moving beyond a sole focus on structural attributes. By concurrently evaluating compressive strength, durability, and sustainability, this framework facilitates the development of eco-friendly bricks that align with both performance and environmental objectives.

The implications of this work extend beyond the current study, providing a foundation for future research to apply the CRITIC–CODAS framework to a broader range of construction materials and large-scale industrial applications. Such efforts can contribute to global sustainability goals, supporting the advancement of net-zero construction practices and fostering the adoption of environmentally responsible materials in the built environment.

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