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INTEGRATING OBJECTIVE WEIGHTING AND PERFORMANCE ANALYSIS FOR SOLVING GREEN ENERGY MANAGEMENT CHALLENGES

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The world is facing an ecological crisis, as carbon emissions from the global construction industry place a significant burden on the environment. Well-designed green energy management (GEM) can mitigate carbon emissions and promote sustainable environmental development. However, assessing green energy involves a complex process of multi-criteria decision-making (MCDM). Traditional approaches cannot accurately account for the objective weight of evaluation criteria, fail to consider the positive and negative ideal solutions of alternatives, and lack an integrated assessment from a multi-dimensional perspective. As a result, the evaluation of green energy remains incomplete. To address these limitations, this study integrates criteria importance through inter-criteria correlation (CRITIC) and the technique for order of preference by similarity to ideal solution (TOPSIS) within a two-dimensional matrix framework to provide managers with decision-making guidance for GEM. A case study on selecting green building insulation materials was conducted to compare the proposed approach with the simple additive weighting (SAW) approach and the TOPSIS approach. The calculation results demonstrate that the proposed approach more accurately evaluates alternative ranking through a visualized framework, offering a more reliable and comprehensive decision-making tool for GEM.

Keywords: Green Energy Management, Criteria Importance Through Inter-Criteria Correlation, Two-Dimensional Matrix, Technique for Order of Preference by Similarity to Ideal Solution.

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1. INTRODUCTION

With the advancement of the industrial era, environmental pollution, the greenhouse effect, and extreme climate events have become major global challenges. Among these, carbon emissions from building energy use have placed a significant burden on the global environment (Ustaoglu *et al*., 2021). Addressing the adverse impacts of energy consumption in the global construction industry on environmental resources and socio-economic development has become an urgent priority (Xu & Wang, 2023). Well-conceived green energy management (GEM) can significantly reduce carbon emissions, facilitate the achievement of sustainable development goals, and alleviate the pressure on global ecosystems. GEM optimizes energy consumption through advanced technologies and encompasses multiple aspects, including energy efficiency, renewable energy integration, sustainable resource utilization, and environmental impact reduction (Krístková *et al*., 2025; Tiwari *et al*., 2024; Arun *et al*., 2024). To enhance energy efficiency, intelligent energy management systems and energy-efficient designs (e.g., passive architecture, thermal insulation) can be implemented alongside low-thermal-conductivity, safety-certified green materials (e.g., insulation, energy-saving bricks) to reduce energy consumption and environmental impact (Patil *et al*., 2022; Wang *et al*., 2025). Regarding renewable energy integration, the adoption of solar photovoltaic building materials, ground-source heat pumps, and small-scale wind power generation enhances the durability and efficiency of renewable energy applications (Elaouzy & El Fadar, 2023; Qiu *et al*., 2023). In the context of sustainable resource utilization, waste heat recovery, smart energy storage, and carbon capture technologies (e.g., green roofs), alongside circular economy-driven recycled materials (e.g., reclaimed concrete, recycled steel, and bamboo-based materials), contribute to resource circularity and carbon reduction objectives (Wang *et al*., 2022b; Liew *et al*., 2021; Mostert *et al*., 2021). Additionally, in terms of environmental impact reduction, the implementation of low-carbon building materials (e.g., low-carbon concrete and natural raw materials), rainwater harvesting systems, and permeable paving, in compliance with green building standards, facilitates carbon emission and pollution mitigation (Wei *et al*., 2024; Wu *et al*., 2025).

An effective GEM strategy and a sound assessment mechanism for the global construction industry can help reduce its carbon footprint and enhance sustainability, thereby mitigating the adverse effects of climate change and resource scarcity.

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In recent years, the adoption of green building materials (GBM) has emerged as a critical issue. For instance, Mayhoub *et al.* (2021) employed the analytic hierarchy process (AHP) to construct a hierarchical framework of evaluation criteria and to determine their relative weights for the selection of green façade materials. Similarly, Balali *et al.* (2020) utilized the step-wise weight assessment ratio analysis (SWARA) method to assign weights to evaluation criteria and applied the complex proportional assessment (COPRAS) technique to rank multiple material alternatives. Moreover, Khoshnava *et al.* (2018) integrated the decision-making trial and evaluation laboratory (DEMATEL) method with the fuzzy analytic network process (FANP) to examine the interrelationships among criteria grounded in the three pillars of sustainability and to prioritize green building material attributes accordingly. A well-designed GBM strategy involves multiple considerations, including increasing recycled content in products to ensure their safety and performance, enabling remanufacturing and high-quality recycling, and reducing carbon and environmental footprints. Each consideration is characterized by unique conditions (Rouyendegh *et al.*, 2020; Grecu *et al.*, 2023). As a result, selecting the most suitable alternative is a complex problem that involves multi-criteria decision-making (MCDM). However, traditional GEM approaches face inherent limitations. They often fail to precisely account for the objective weighting of evaluation criteria and do not consider the positive and negative ideal solutions of alternatives. Furthermore, they lack a multi-dimensional perspective for analyzing the evaluation criteria of alternatives, limiting their ability to provide decision-making support for managers.

Commonly employed approaches to address the issue of objective weighting in MCDM include principal component analysis (PCA), entropy, and criteria importance through inter-criteria correlation (CRITIC), all of which are utilized to determine the importance of assessment criteria. Among these, the CRITIC approach is particularly well-suited for resolving practical problems that require balancing conflicting criteria. It determines weights based on data from the existing decision matrix, eliminating human intervention. This feature minimizes potential biases arising from subjective assessments and significantly enhances the objectivity of the evaluation process (Diakoulaki *et al.*, 1995). For example, Haktanır and Kahraman (2022) formulated the picture fuzzy CRITIC approach and applied it to evaluate wearable health technology. Similarly, Wang *et al.* (2022a) combined the grey relational projection and CRITIC approaches to address the site selection problem for hospital construction. Additionally, Simic *et al.* (2022) integrated the CRITIC method with a type-2 neutrosophic model based on multi-attribute border approximation area comparison to assess the importance of criteria in selecting a public transportation pricing system. To date, many studies continue to apply the CRITIC method to address MCDM problems in various fields (e.g., Qian *et al.*, 2025; Razzaq *et al.*, 2025; Su *et al.*, 2025).

In the past, various approaches have been employed to address challenges in processing quantitative information. These include the technique for order of preference by similarity to ideal solution (TOPSIS), the preference ranking organization method for enrichment evaluation (PROMETHEE), the weighted product model (WPM), and the simple additive weighting (SAW). Among these, the TOPSIS method promotes balanced decision-making by considering both the shortest distance to the positive ideal solution (PIS) and the greatest distance from the negative ideal solution (NIS), enabling decision-makers to identify the optimal alternative with minimal ambiguity. For example, Asadabadi *et al.* (2023) integrated the best-worst method and TOPSIS to develop an innovative standardized decision-making framework designed to assist organizations in supplier evaluation while accounting for potential future events. Wątróbski *et al.* (2022) introduced a novel method for sustainability assessment, combining data variability evaluation with the TOPSIS approach to assess sustainable cities and communities across 26 European countries. Similarly, Zaman *et al.* (2023) applied the Fermatean fuzzy extended TOPSIS method to solve a multi-attribute group decision-making problem in selecting teachers. The TOPSIS method is currently widely applied to solve decision-making problems in various industries (e.g., Wen *et al.*, 2021; Zheng *et al.*, 2025; Liu *et al.*, 2025; Lin and Chang, 2025).

The importance-performance analysis (IPA) approach is among the most extensively utilized techniques for achieving a multi-dimensional perspective in evaluation. This approach uses mean values as the central coordinates of a matrix, evaluating importance along the vertical axis and performance (or satisfaction) along the horizontal axis, thereby dividing the matrix into four quadrants. Within this two-dimensional evaluation framework, the relative positioning of alternatives provides valuable insights for strategic adjustments and recommendations (Martilla & James, 1977). By leveraging this matrix, the IPA approach offers a comprehensive foundation for decision-making, enabling actionable recommendations based on the quadrant distribution of the alternatives. For example, Chen *et al.* (2022) used the IPA approach to analyze the satisfaction levels of target groups with social media. Similarly, Joung and Kim (2021) utilized the IPA approach to identify product attributes based on online product design reviews. Zheng and Chang (2025) combined IPA with the ordered weighted averaging operator to propose a novel functional movement ability assessment method aimed at addressing sports injury risk assessment for athletes. Additionally, Cladera (2022) employed the IPA approach to provide teachers with an intuitive understanding of how teaching attributes are perceived by learners, facilitating a more targeted approach to educational improvement.

To address the limitations of traditional methods, this study integrates objective weighting of assessment criteria with quantitative data processing to evaluate GEM. The proposed approach employs the CRITIC method to determine the objective weights of the criteria and applies the TOPSIS method to rank potential alternatives, thereby enhancing the rationality and practical relevance of the analysis. Additionally, the approach adopts the two-dimensional matrix concept of the IPA approach, categorizing alternatives into four quadrants and visualizing the data to provide managers with actionable decision-making support. The theoretical and practical contributions of this approach are as follows:

1. Objective weighting of assessment criteria: By incorporating precise objective weights, the ranking results become more reliable.
2. Consideration of PIS and NIS: The approach accounts for the longest distance from the NIS and the shortest distance to the PIS, ensuring effective decision-making.
3. Two-dimensional analysis: The approach processes two-dimensional information to generate a strategic matrix, offering recommendations and insights for GEM.

The subsequent sections of this study are organized as follows: Section 2 provides an overview of the fundamental definitions and computational rules of the CRITIC approach, the TOPSIS approach, and the two-dimensional matrix. Section 3 introduces the proposed approach for green energy assessment, detailing its implementation steps. Section 4 evaluates the innovation and effectiveness of the proposed approach through a practical case study, comparing the simulation results with those of other methods. Finally, Section 5 presents the study's conclusion and suggests avenues for future research.

2. PRELIMINARIES

2.1 CRITIC approach

Diakoulaki *et al*. (1995) proposed the CRITIC approach to determine the objective weights of evaluation criteria. The technique employs standard deviation and correlation coefficients to account for both the variability and the conflict among criteria. A higher standard deviation for an evaluation criterion indicates greater variability and contrast intensity, leading to a higher assigned weight. Additionally, the correlation coefficient measures the conflict between two criteria. A higher positive correlation suggests greater similarity in the information provided by the criteria when evaluating alternatives, indicating lower conflict and, consequently, a lower assigned weight. The CRITIC approach consists of six steps, as described below (Peng & Garg, 2022; Li *et al*., 2022; Wu *et al*., 2021).

Step 1: Create an initial decision matrix (D).

The decision matrix D is formed as follows:

$$D = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1j} & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2j} & x_{2n} \\ \vdots & \vdots & \cdots & \vdots & \vdots \\ x_{i1} & x_{i2} & \cdots & x_{ij} & x_{in} \\ x_{m1} & x_{m2} & \cdots & x_{mj} & x_{mn} \end{bmatrix} \tag{1}$$

where x_{ij} denotes the value of the *j-th* criterion for the *i-th* alternative.

Step 2: Normalize the initial decision matrix.

To ensure data consistency, the raw values are normalized by transforming them onto a standardized scale ranging from 0 to 1.

$$r_{ij} = \begin{cases} \dfrac{x_{ij} - x_j^{min}}{x_j^{max} - x_j^{min}}, & if\ j \in benefit\ criteria \\ \dfrac{x_j^{max} - x_{ij}}{x_j^{max} - x_j^{min}}, & if\ j \in cost\ criteria \end{cases} \tag{2}$$

where r_{ij} represents the normalized value of alternative i with respect to criterion j, while x_j^{max} and x_j^{min} denotes the maximum and minimum value of criterion j, respectively.

Step 3: Calculate the variability of each criterion.

The standard deviation (s_j) of the j-th column reflects the contrast intensity of that criterion. A larger s_j value indicates greater variability among evaluation criteria, leading to a higher assigned weight.

$$s_j = \sqrt{\frac{\sum_{i=1}^{m}\left(r_{ij} - \bar{r}_j\right)^2}{m-1}} \tag{3}$$

where $\bar{r}_j$ represents the mean value of the *j*th column, and *m* denotes the total number of alternatives.

Step 4: Compute the conflict of each criterion.

The Pearson correlation coefficient (ρ_{jk}) quantifies the degree of conflict between the *j*-th and *k*-th columns. Higher values of ρ_{jk} indicate lower conflict between the criteria, resulting in a smaller assigned weight.

$$\rho_{jk} = \frac{\sum_{i=1}^{m}\left(r_{ij} - \bar{r}_j\right)\cdot\left(r_{ik} - \bar{r}_k\right)}{\sqrt{\sum_{i=1}^{m}\left(r_{ij} - \bar{r}_j\right)^2 \cdot \sum_{i=1}^{m}\left(r_{ik} - \bar{r}_k\right)^2}} \tag{5}$$

where $\bar{r}_j$ and $\bar{r}_k$ denote the mean values of the *j*-th and *k*-th columns, respectively.

Step 5: Compute the information content.

The information content of the j-th criterion (c_j) is determined by integrating its standard deviation and the degree of conflict with other criteria.

$$c_j = s_j \cdot \sum_{k=1}^{n}\left(1 - \rho_{jk}\right) \tag{5}$$

Step 6: Calculate the weight coefficients.

The weight coefficient w_j of the *j*-th objective is obtained as follows:

$$w_j = \frac{c_j}{\sum_{k=1}^{n} c_j} \tag{6}$$

2.2 TOPSIS approach

The TOPSIS technique, developed by Hwang and Yoon (1981), has been widely applied to solve MCDM problems. This approach determines the distances between each alternative and both the positive ideal solution PIS (A^{+}) and the negative ideal solution NIS (A^{-}), then ranks the alternatives based on these distances. It can be used to evaluate the decision matrix represented by Equation (7), where x_{ij} denotes the value of the *j*-th criterion for the *i*-th alternative. The implementation process consists of the following steps (Venugopal *et al.*, 2024; Corrente & Tasiou, 2023; Wang *et al.*, 2022c):

$$D = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1j} & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2j} & x_{2n} \\ \vdots & \vdots & \cdots & \vdots & \vdots \\ x_{i1} & x_{i2} & \cdots & x_{ij} & x_{in} \\ x_{m1} & x_{m2} & \cdots & x_{mj} & x_{mn} \end{bmatrix} \tag{7}$$

Step 1: Compute the normalized evaluation matrix.

The normalized value r_{ij} is calculated as:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}, \quad j = 1, 2, \ldots, n; \quad i = 1, 2, \ldots, m \tag{8}$$

Step 2: Compute the PIS (A^{+}) and the NIS (A^{-}).

$$A^{+} = \{{v_1}^{+}, {v_2}^{+}, \ldots, {v_n}^{+}\} = \left\{\left(\max_j v_{ij} \mid i \in J\right), \left(\min_j v_{ij} \mid i \in J'\right)\right\}, \tag{9}$$

$$A^{-} = \{v_1^{-}, v_2^{-}, \dots, v_n^{-}\} = \left\{\left(\min_j v_{ij} \mid i \in J\right), \left(\max_j v_{ij} \mid i \in J'\right)\right\}, \tag{10}$$

where J represents the benefit criterion and J' represents the benefit criterion and cost criterion. A higher index value of J indicates better performance, whereas a lower index value of J' indicates better performance.

Step 3: Compute the separation measures using the n-criterion Euclidean distance.
The separation from the PIS (D_i^{+}) and the NIS (D_i^{-}) for each alternative is computed as:

$$D_i^{+} = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^{+})^2}, \quad i = 1, 2, \dots, m \tag{11}$$

$$D_i^{-} = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^{-})^2}, \quad i = 1, 2, \dots, m \tag{12}$$

Step 4: Compute the relative closeness of each alternative to the ideal solution.

$$C_i = \frac{D_i^{-}}{D_i^{+} + D_i^{-}} \tag{13}$$

where $0 \le C_i \le 1$, and $i = 1, 2, \dots, m$. A C_i value closer to 1 indicates a solution closer to A^{+}.
Step 5: Rank the alternatives in descending order of C_i.
A higher C_i value corresponds to a more preferred alternative.

2.3 Two-dimensional matrix

The concept of the two-dimensional matrix originates from the IPA approach proposed by Martilla and James (1977). The IPA approach partitions the two-dimensional matrix into four quadrants, each centered on data points, with threshold values determined by the alternatives' average importance and performance scores. The vertical axis represents importance, while the horizontal axis represents performance, offering decision-making guidance for organizations or businesses (Rašovská *et al*., 2021; Nguyen *et al*., 2022), as illustrated in Figure 1.

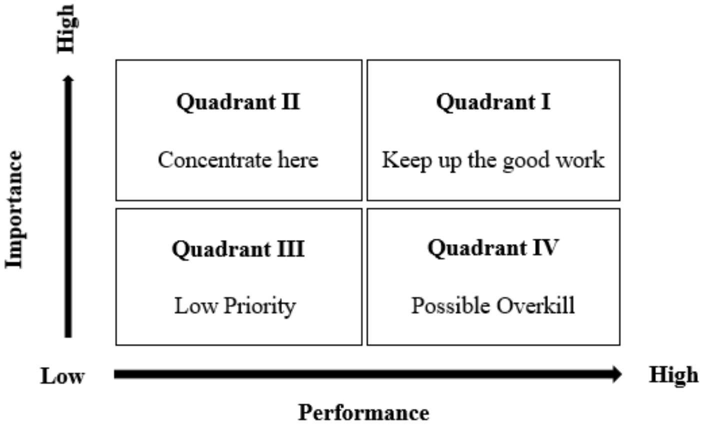

Figure 1. Two-dimensional matrix from the IPA

The attributes of each quadrant are as follows:

(1) Quadrant I represents high performance and high importance, indicating alternatives that enhance organizational competitiveness or provide a competitive advantage. Businesses should "keep up the good work" in this area.

(2) Quadrant II represents high importance but low performance, labeled as "concentrate here," highlighting alternatives that require immediate attention and resource allocation to improve performance and enhance customer satisfaction.

(3) Quadrant III represents low performance and low importance, often categorized as "low priority." Businesses do not need to allocate significant resources to the alternatives in this quadrant.
(4) Quadrant IV represents low importance but high performance, referred to as "possible overkill," suggesting that resources allocated here might be more effectively utilized elsewhere.

3. METHODOLOGY

3.1 Research Framework

The escalating severity of extreme climate change has placed a substantial environmental burden on the global construction industry due to its energy consumption and carbon emissions. Effective GEM must simultaneously enhance environmental performance and reduce environmental burden to achieve lower carbon footprints, improve energy efficiency, and foster a sustainable built environment. However, traditional GEM approaches exhibit several limitations:

(1) Lack of precise consideration for criteria weights: Traditional approaches do not account for the precise objective weight of all evaluation criteria, failing to indicate their relative importance. This simplification undermines the reliability of decision-making and adversely affects the quality and credibility of outcomes.
(2) Failure to address the complexity of alternatives: Conventional approaches do not consider the shortest distance to the PIS and the longest distance to the NIS, which may introduce biases in the final ranking outcomes.
(3) Absence of multi-dimensional perspectives: Traditional approaches often employ a one-dimensional evaluation approach for alternative ranking, which is inadequate for capturing the complexity and diversity of multi-dimensional evaluation criteria. This results in the incomplete representation of the attributes and distribution of alternative options, limiting resource allocation and impairing decision-making recommendations.

To address these limitations, this study integrated the CRITIC, TOPSIS, and IPA approaches into a comprehensive two-dimensional evaluation framework to enhance the decision-making for GEM. First, the CRITIC approach was employed to determine the weights of the assessment criteria, simultaneously considering contrast intensity and conflicting relationships to improve the accuracy of the selection process. Second, the TOPSIS approach ranks alternatives by evaluating their distances to the PIS and NIS, offering more reliable decision-making recommendations. Finally, to facilitate multi-dimensional analysis, the proposed framework incorporates a two-dimensional visualization method that graphically presents each alternative's attributes within four quadrants, as illustrated in Figure 2.

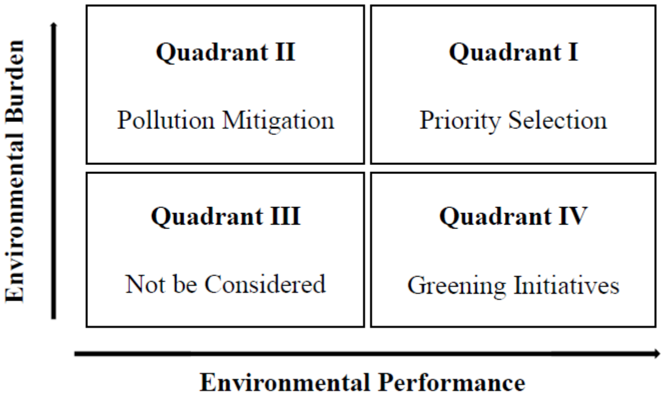

Figure 2. Research framework.

3.2 Research Design

The implementation steps of the proposed approach, which integrates the CRITIC, TOPSIS, and IPA methods, are illustrated in Figure 3. In Phase I, the CRITIC method objectively determines the weights of the evaluation criteria by considering both the contrast intensity and the conflict among criteria. These objective weights are then carried forward to Phase II, where they are integrated into the TOPSIS method to rank alternatives based on their relative closeness to the ideal solution, ensuring that the ranking process is objective and data-driven. In Phase III, the results of the CRITIC and TOPSIS analyses are jointly visualized using a two-dimensional IPA diagram, transforming complex quantitative assessments into an intuitive visual representation to facilitate managerial interpretation and strategic decision-making.

Phase I. Determining objective weights using the CRITIC approach

Step 1. Define dimensions and assessment criteria and collect alternative data.

Through discussions with experts, the appropriate dimensions and evaluation criteria are identified. The quantitative values of the potential alternatives are determined based on their capacity to enhance environmental performance and mitigate environmental burdens. An initial decision matrix is then constructed using Equation (1).

Step 2. Normalize the initial decision matrix.

Following Step 1, the values in the initial decision matrix are normalized using Equation (2) to standardize the data for subsequent analysis.

Step 3. Calculate standard deviation, correlation coefficient, and information content to derive objective weights.

Based on the results of Step 2, the standard deviation is calculated using Equation (3), the Pearson correlation coefficient is computed using Equation (4), and information content is determined using Equation (5). Finally, Equation (6) is applied to calculate the objective weights for each criterion, ensuring a rigorous weighting process.

Phase II. Ranking alternatives using the integrated CRITIC-TOPSIS approach

Step 4: Compute the normalized matrix.

Based on the quantitative values of the potential alternatives, Equation (8) is used to compute the normalized values (r_{ij}).

Step 5: Determine the PIS ($A+$) and NIS ($A-$).

Using the objective weights derived in Step 3, Equations (9) and (10) are employed to calculate $A+$ and $A-$.

Step 6: Compute separations and the relative closeness of each alternative to the ideal solutions.

Equations (11) and (12) are used to calculate the separations of each alternative from the PIS (D_i^+) and NIS (D_i^-). Equation (13) is then applied to compute the relative closeness (C_i), where a higher C_i value indicates greater proximity to the PIS.

Phase III. Constructing a 2D decision-making diagram using the integrated CRITIC-TOPSIS-IPA approach

Step 7. Develop a two-dimensional diagram for decision-making support.

Using the results from Step 2 and Step 3, a two-dimensional diagram is constructed to visually represent the environmental benefits and burdens of each alternative. This visualization serves as a valuable decision-making tool for managers, aiding in the selection of the most suitable solution.

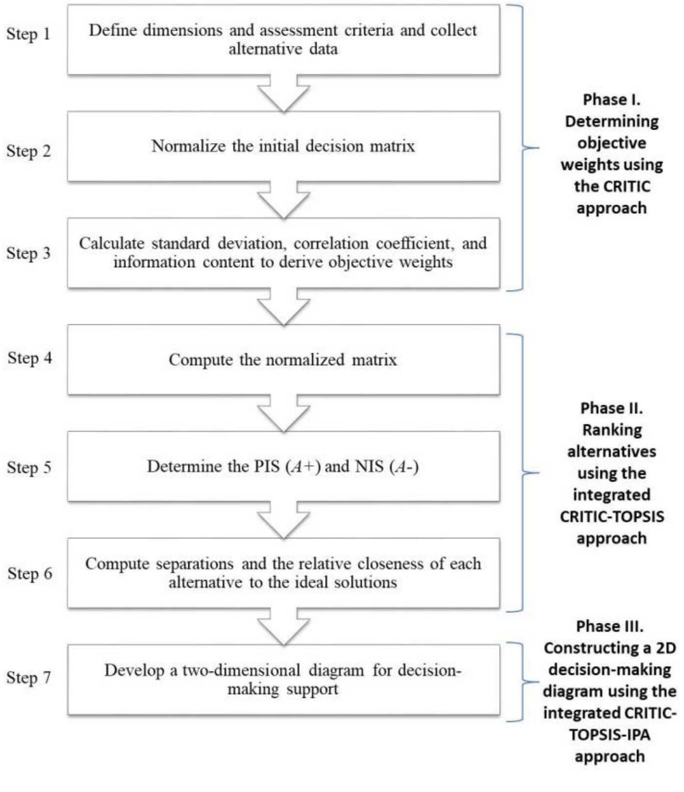

Figure 3. Flowchart for the proposed GEM approach

4. CASE STUDY

4.1 Summary of numerical examples

As global green technologies continue to advance, the construction industry is undergoing significant innovation and transformation. GBM plays a crucial role in reducing carbon emissions, supporting the attainment of sustainable development goals, and mitigating stress on global ecosystems. The selection of an optimal GBM requires consideration of numerous evaluation criteria, making it an MCDM problem. Therefore, an effective evaluation framework is essential for selecting appropriate materials. To demonstrate the effectiveness of the proposed approach, this study utilized a green building insulation materials selection case adapted from Grecu *et al*. (2023) to evaluate and validate the efficacy and rationality of the approach. The case examined nine GBM in the European market, each characterized by distinct typologies, including aerogel insulation (GBM1), insulation material primarily composed of cork (GBM2), diathonite thermactive (GBM3), bio-composite material based on natural hemp fibers (GBM4), wool-type insulation material (GBM5), insulation material made of recyclable content (GBM6), glass mineral-blowing wool (GBM7), rock mineral wool (GBM8), and glass mineral wool (GBM9).

The material selection process is guided by two evaluation dimensions: enhanced environmental performance (EP) and reduced environmental burden (EB), which are quantitatively assessed based on the characteristics of the material types. The EP dimension comprises three criteria: fire-resistance rating (C1), water vapor diffusion resistance coefficient (C2), and recycled content (C3). Building materials are designed to withstand fire and not produce heavy smoke. C1 is assessed on a scale from 0 to 10, with higher scores indicating greater fire resistance. The vapor barrier must also protect the insulation from moisture.

C2 reflects a material's ability to impede water vapor transmission and is expressed as the μ-value — a temperature-dependent, dimensionless property, with higher values indicating greater effectiveness as a vapor barrier. Furthermore, resource recycling and reuse contribute to environmental sustainability. C3 is assessed on a scale from 0 to 1, indicating the proportion of recycled material in the composition, with higher values reflecting a more favorable environmental impact. Finally, the EB dimension consists of two criteria: thermal conductivity (C4) and global warming potential (C5). C4 measures a material's thermal conductivity, expressed in watts per meter per kelvin (W/m·K), where lower values indicate better insulation performance. This helps maintain a stable indoor temperature, thereby reducing energy consumption and environmental impact. C5 quantifies the carbon emissions generated during the manufacturing process, expressed in kilograms of carbon dioxide equivalent (kgCO$_2$ eq), with lower values indicating a reduced environmental burden. These criteria comprehensively assess the ecological sustainability of the materials, as detailed in Table 1.

Table 1**.** The test data for the nine materials' assessment criteria

Materials	EP			EB	
	C1	C2	C3	C4	C5
GBM1	6.000	5.000	0.200	0.015	12.300
GBM2	8.000	10.000	0.000	0.052	0.076
GBM3	10.000	3.000	0.412	0.037	0.895
GBM4	2.000	2.300	0.120	0.040	2.220
GBM5	2.000	1.800	0.200	0.061	0.110
GBM6	2.000	1.000	0.950	0.040	0.990
GBM7	10.000	1.000	0.800	0.033	2.920
GBM8	10.000	1.000	0.280	0.037	7.610
GBM9	10.000	1.000	0.000	0.032	1.500

4.2 Solution by the SAW approach

The SAW approach (Muddineni *et al*., 2017) is a straightforward and widely used MCDM technique. It involves normalizing the values in the original decision matrix to ensure consistency across different evaluation criteria. For benefit criteria, each value is divided by the maximum value of the corresponding criterion, while for cost criteria, the minimum value of the criterion is divided by each value, as shown below.

$$N_{ij} = \begin{cases} \dfrac{x_{ij}}{Max_i x_{ij}}, & if\ j \in benefit\ criteria \\ \dfrac{Min_i x_{ij}}{x_{ij}}, & if\ j \in cost\ criteria \end{cases} \tag{14}$$

The SAW value for each alternative is then calculated as follows:

$$SAW_i = \sum_{j=1}^{n} w_j \cdot N_{ij}, \quad i = 1,2,\dots,m \tag{15}$$

Each criterion is assigned an equal weight. Using Equations (14) and (15), the normalized values for each alternative are computed and summed to determine a ranking. Within the EP dimension, C1 to C3 are classified as benefit criteria, where higher values are preferred. Conversely, within the EB dimension, C4 to C5 are designated as cost criteria, where lower values are more desirable. Although the SAW approach is computationally simple, it does not account for the objective weight of evaluation criteria, limiting its accuracy in ranking materials. Based on Table 1, the ranking results for the nine materials obtained using the SAW approach are presented in Table 2.

Table 2. The SAW value for the nine materials by the SAW approach

Materials	EP			EB		SAW value	Ranking
	C1	C2	C3	C4	C5		
GBM1	0.600	0.500	0.211	1.000	0.006	0.463	3
GBM2	0.800	1.000	0.000	0.288	1.000	0.618	1
GBM3	1.000	0.300	0.434	0.405	0.085	0.445	4
GBM4	0.200	0.230	0.126	0.375	0.034	0.193	9
GBM5	0.200	0.180	0.211	0.246	0.691	0.305	8
GBM6	0.200	0.100	1.000	0.375	0.077	0.350	6
GBM7	1.000	0.100	0.842	0.455	0.026	0.485	2
GBM8	1.000	0.100	0.295	0.405	0.010	0.362	5
GBM9	1.000	0.100	0.000	0.469	0.051	0.324	7

4.3 Solution by the TOPSIS approach

The TOPSIS approach (Iqbal, 2021) effectively analyzes quantitative data using its computational characteristics, providing accurate rankings and identifying the optimal solution. Based on Table 1, Equation (8) is used to normalize the assessment criteria C1-C5 in the initial decision matrix, resulting in the normalized decision matrix. The calculated results are presented in Table 3.

Table 3. Normalized decision matrix by the TOPSIS approach

Materials	EP			EB	
	C1	C2	C3	C4	C5
GBM1	0.265	0.413	0.146	0.124	0.817
GBM2	0.354	0.826	0.000	0.429	0.005
GBM3	0.442	0.248	0.300	0.305	0.059
GBM4	0.088	0.190	0.087	0.330	0.147
GBM5	0.088	0.149	0.146	0.503	0.007
GBM6	0.088	0.083	0.692	0.330	0.066
GBM7	0.442	0.083	0.583	0.272	0.194
GBM8	0.442	0.083	0.204	0.305	0.505
GBM9	0.442	0.083	0.000	0.264	0.100

Subsequently, using the results in Table 2 and assuming equal weights for all evaluation criteria, Equations (9) to (10) are used to calculate the PIS (A^+) and the NIS (A^-) for each material. Among these, criteria C1 to C3 under the EP dimension are classified as benefit criteria, where higher values are more favorable. Conversely, criteria C4 to C5 under the EB dimension are classified as cost criteria, where lower values are preferred. The detailed calculation results are presented in Table 4.

Table 4. Weighted normalized decision matrix by the TOPSIS approach

Materials	EP			EP	
	C1	C2	C3	C4	C5
GBM1	0.053	0.083	0.029	0.025	0.163
GBM2	0.071	0.165	0.000	0.086	0.001
GBM3	0.088	0.050	0.060	0.061	0.012
GBM4	0.018	0.038	0.017	0.066	0.029
GBM5	0.018	0.030	0.029	0.101	0.001
GBM6	0.018	0.017	0.138	0.066	0.013
GBM7	0.088	0.017	0.117	0.054	0.039
GBM8	0.088	0.017	0.041	0.061	0.101
GBM9	0.088	0.017	0.000	0.053	0.020
A^+	0.088	0.165	0.138	0.025	0.001
A^-	0.018	0.017	0.000	0.101	0.163

Finally, based on the results in Table 4, Equations (11) to (13) are used to calculate the D_i^+, D_i^-, and C_i values for different materials. The detailed results are presented in Table 5. For example, the D_i^+ value for Material GBM2 is 0.152, and the D_i^- value is 0.227. Using Equation (13), the C_i value is calculated as 0.598, indicating that Material M2 is more suitable for prioritization and adoption:

$$C_i = \frac{{D_i}^-}{{D_i}^+ + {D_i}^-} = \frac{0.227}{0.152 + 0.227} = 0.598$$

Table 5. The separation measures and the relative closeness to the ideal solution

Materials	D_i^+	D_i^-	C_i	Ranking
GBM1	0.215	0.111	0.339	9
GBM2	0.152	0.227	0.598	1
GBM3	0.145	0.185	0.561	2
GBM4	0.196	0.141	0.419	7
GBM5	0.203	0.165	0.449	5
GBM6	0.170	0.207	0.549	3
GBM7	0.158	0.190	0.547	4
GBM8	0.207	0.110	0.347	8
GBM9	0.206	0.167	0.448	6

4.4 Solution by the proposed approach

Selecting an appropriate GBM can significantly reduce carbon emissions, mitigate air pollution, and promote environmental sustainability. However, traditional GBM selection methods have several limitations, such as ignoring the relative weight between evaluation criteria, failing to consider the PIS and NIS of alternatives, and lacking a multi-dimensional perspective. To address these limitations, this study integrated the CRITIC and TOPSIS approaches, leveraging the two-dimensional evaluation perspective of the IPA approach. This comprehensive approach provides managers with well-informed selection recommendations. The methodology consists of three phases and seven steps.

Phase I. Determining the objective weights using the CRITIC approach

Step 1. Define dimensions and evaluation criteria, and collect material data.

Through expert discussions, two primary dimensions for GBM selection were identified: environmental performance and environmental burden. Five assessment criteria (C1-C5) were established, and quantitative data for nine potential GBMs (GBM1-GBM9) were collected, as demonstrated in Table 1.

Step 2. Normalize the initial decision matrix.

Using data in Table 1, Equation (2) was applied to compute the normalized decision matrix. The detailed calculation results are presented in Table 6.

Table 6. Normalized decision matrix of materials' selection

Materials	EP			EB	
	C1	C2	C3	C4	C5
GBM1	0.500	0.444	0.211	1.000	0.000
GBM2	0.750	1.000	0.000	0.196	1.000
GBM3	1.000	0.222	0.434	0.522	0.933
GBM4	0.000	0.144	0.126	0.457	0.825
GBM5	0.000	0.089	0.211	0.000	0.997
GBM6	0.000	0.000	1.000	0.457	0.925
GBM7	1.000	0.000	0.842	0.609	0.767
GBM8	1.000	0.000	0.295	0.522	0.384
GBM9	1.000	0.000	0.000	0.630	0.884

Step 3. Calculate standard deviation, correlation coefficient, and information content to derive objective weights.

Using Table 6, Equations (3)–(6) were applied to calculate the Pearson correlation coefficient, standard deviation (s_j), and the information content (c_j). These values quantify the variability and conflict within each criterion, enabling the derivation of objective weights (w_j). The results are presented in Table 7.

Table 7. The values of s_j, c_j, and w_j for each assessment criterion

	C1	C2	C3	C4	C5
C1	1.000	0.070	-0.108	0.352	-0.158
C2	0.070	1.000	-0.459	-0.142	-0.003
C3	-0.108	-0.459	1.000	0.121	0.081
C4	0.352	-0.142	0.121	1.000	-0.758
C5	-0.158	-0.003	0.081	-0.758	1.000
s_j	0.468	0.331	0.355	0.279	0.337
c_j	1.798	1.499	1.550	1.237	1.630
w_j	0.233	0.194	0.201	0.160	0.211

Phase II. Ranking materials using the integrated CRITIC-TOPSIS approach

Step 4: Compute the normalized matrix.

Using Equation (8) and the quantitative values from Table 1, the normalized values (r_{ij}) were calculated. The detailed results of the calculations are presented in Table 2.

Step 5: Determine the PIS (A+) and NIS (A-).

Based on the objective weights in Table 7, Equations (9) and (10) were applied to compute A^+ and A^-. The detailed calculation results are presented in Table 8.

Table 8. Weighted normalized decision matrix by the CRITIC-TOPSIS approach

Materials	EP			EB	
	C1	C2	C3	C4	C5
GBM1	0.062	0.080	0.029	0.020	0.173
GBM2	0.082	0.161	0.000	0.069	0.001
GBM3	0.103	0.048	0.060	0.049	0.013
GBM4	0.021	0.037	0.018	0.053	0.031
GBM5	0.021	0.029	0.029	0.081	0.002
GBM6	0.021	0.016	0.139	0.053	0.014
GBM7	0.103	0.016	0.117	0.044	0.041
GBM8	0.103	0.016	0.041	0.049	0.107

Materials	EP			EB	
	C1	C2	C3	C4	C5
GBM9	0.103	0.016	0.000	0.042	0.021
A^{+}	0.103	0.161	0.139	0.020	0.001
A^{-}	0.021	0.016	0.000	0.081	0.173

Step 6: Compute separations and the relative closeness of each alternative to the ideal solutions.

Using Equations (11) to (13), the separation distances of each material from the PIS (D_i^{+}) and NIS (D_i^{-}), along with the relative closeness (C_i), were calculated. The detailed calculation results are shown in Table 9.

Table 9. Separation measures and relative closeness to the ideal solution using the CRITIC-TOPSIS approach

Materials	D_i^{+}	D_i^{-}	C_i	Ranking
GBM1	0.223	0.102	0.314	9
GBM2	0.149	0.233	0.610	1
GBM3	0.141	0.195	0.581	2
GBM4	0.197	0.147	0.427	7
GBM5	0.200	0.174	0.466	6
GBM6	0.170	0.213	0.556	4
GBM7	0.153	0.198	0.563	3
GBM8	0.206	0.118	0.363	8
GBM9	0.203	0.177	0.466	5

Phase III. Developing a 2D diagram using the integrated CRITIC-TOPSIS-IPA approach

Step 7: Construct a two-dimensional plot.

The IPA framework is applied to introduce a multi-dimensional evaluation perspective. Using the normalized values from Table 6 and the objective weights from Table 7, the EP and EB dimensions serve as the evaluation indicators for the *X*-axis and *Y*-axis, respectively. The average EP and EB values across all materials were computed to determine the central coordinates of the four quadrants in the two-dimensional graph. This data visualization helps identify the distribution of each material and enables a comparative analysis of the strengths and weaknesses across the alternatives. The detailed results are shown in Table 10 and illustrated in Figure 4.

Table 10. The distribution of all materials in the quadrants

Materials	EP	EB	Quadrant
GBM1	0.393	0.446	III
GBM2	0.593	0.641	I
GBM3	0.585	0.750	I
GBM4	0.084	0.661	II
GBM5	0.093	0.553	III
GBM6	0.312	0.716	II
GBM7	0.644	0.697	I
GBM8	0.474	0.445	IV
GBM9	0.382	0.771	II

This two-dimensional framework visualizes the positioning of nine GBM alternatives based on EP and EB, enabling decision-makers to identify trade-offs, prioritize alternatives, and implement targeted improvement strategies. The center point of the X-axis (0.396) is determined by the average value of the EP dimension across GBM1 to GBM9, while the average value of the EB dimension determines the center point of the Y-axis (0.631).

The decision-making support and recommendations for managers are as follows:

(1) Quadrant I: Materials in this quadrant exhibit advantages in both the EP and EB dimensions. The evaluation results indicate that GBM2, GBM3, and GBM7 offer dual benefits by enhancing environmental performance while reducing environmental burdens. It is recommended that managers prioritize these materials.

(2) Quadrant II: Materials in this quadrant have relatively lower EP but stronger EB attributes. The evaluation results reveal that GBM4, GBM6, and GBM9 effectively reduce environmental pollution and carbon emissions during

manufacturing but perform poorly in terms of future renewable energy utilization. If these materials must be used, comprehensive supporting measures should be developed to enhance resource regeneration and environmental sustainability.

(3) Quadrant III: Materials in this quadrant show disadvantages in both EP and EB dimensions, rendering them unsuitable for selection. Evaluation results suggest that GBM1 and GBM5 should be excluded from consideration.

(4) Quadrant IV: Materials in this quadrant have relatively lower EB but stronger EP. The evaluation results show that M8 performs better in terms of energy regeneration and environmental sustainability, but contributes to higher ecological pollution during manufacturing. If the use of these materials is unavoidable, supplementary measures should be implemented to mitigate pollution sources effectively.

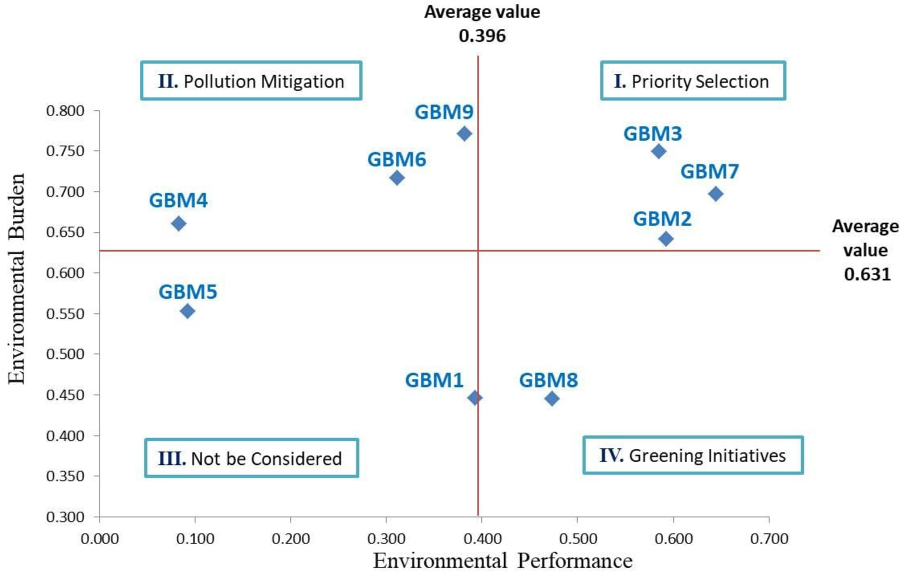

Figure 4. The distribution of all materials in the two-dimensional framework

4.5 Discussion

This study applied the proposed approach to a GBM selection case to assess its efficacy and rationale, comparing the ranking results with those obtained using the SAW and typical TOPSIS methods. Additionally, the benefits of the proposed approach are summarized, with the results presented in Tables 11 and 12.

(1) Determine the objective weights for the assessment criteria.

The SAW and typical TOPSIS methods, both widely used MCDM techniques, were used to evaluate quantitative problems. However, these approaches do not calculate objective weights for assessment criteria, potentially leading to biased results. To address this limitation, the proposed method incorporates the advantages of the CRITIC method, which assesses the contrast intensity and conflicting relationships among criteria. This ensures a more accurate calculation of objective weights, thereby enhancing the objectivity of the final ranking results.

(2) Consider the PIS and NIS.

The SAW method evaluates alternatives based solely on their overall attributes, which may introduce ranking biases. In contrast, both the TOPSIS method and the proposed approach consider the shortest distance to the PIS and the longest distance to the NIS. This improves the reliability of material evaluation by ensuring that the ranking reflects the relative closeness of alternatives to the ideal solution.

(3) Generate 2D graphics to provide a reference.

The SAW and typical TOPSIS methods rely on one-dimensional evaluation approaches for material ranking. However, these methods lack multi-dimensional assessment capabilities, making it difficult to effectively illustrate the distribution of material attributes. The proposed approach addresses this limitation by incorporating a two-dimensional framework and constructing a visual graph. This classification method highlights differences in the EP and EB dimensions, offering a clear visual representation. Additionally, it provides decision-making support for managers by identifying the strengths and weaknesses of materials within the four-quadrant framework.

Table 11. Comparison of rankings by the three approaches

Materials	SAW approach		TOPSIS approach		Proposed approach		
	SAW value	Ranking	C_i value	Ranking	SAW value	Ranking	C_i value
GBM1	0.463	3	0.339	9	0.314	9	III
GBM2	0.618	1	0.598	1	0.610	1	I
GBM3	0.445	4	0.561	2	0.581	2	I
GBM4	0.193	9	0.419	7	0.427	7	II
GBM5	0.305	8	0.449	5	0.466	6	III
GBM6	0.350	6	0.549	3	0.556	4	II
GBM7	0.485	2	0.547	4	0.563	3	I
GBM8	0.362	5	0.347	8	0.363	8	IV
GBM9	0.324	7	0.448	6	0.466	5	II

Table 12. Differences in information processing of the three different approaches

Research Approach	Calculate the objective weights by considering the contrast intensity and conflicting relationships.	Consider the shortest distance to the PIS and the longest distance to the NIS.	Generate 2D graphics to provide a reference.
SAW approach (Muddineni *et al*., 2017)	No	No	No
TOPSIS approach (Iqbal, 2021)	No	Yes	No
Proposed approach	Yes	Yes	Yes

5. CONCLUSION

Carbon emissions from the construction industry significantly impact the ecological environment. By implementing effective GEM strategies, corporate and organizational decision-makers can reduce carbon emissions and promote environmental sustainability. However, traditional approaches do not accurately account for the objective weights of evaluation criteria, fail to consider the PIS and NIS of alternatives, and lack a multi-dimensional perspective for alternative selection. To address these limitations, this study integrated the CRITIC and TOPSIS approaches within a two-dimensional framework, introducing a novel GEM approach. This approach incorporates visual analysis, providing more detailed insights for managerial decision-making.

The key contributions of this study are as follows:

(1) Theoretical contribution

The proposed approach enables a more precise computation of the objective weights of assessment criteria while simultaneously considering the characteristics of the PIS and NIS, thereby enhancing its ability to process quantitative information. Additionally, it utilizes available data to construct a two-dimensional graph, offering valuable insights to support decision-making in GEM.

(2) Practical contribution

The world is facing an ecological crisis, with carbon emissions from global building energy consumption being a significant contributing factor. This study presents a novel evaluation framework using GBM as a case study. Through visualized graphical representations, the framework allows managers to gain a more comprehensive and intuitive understanding of the attribute distribution of alternative options, thereby facilitating reliable and accurate decision-making.

Although the proposed method accounts for the objective weights of evaluation criteria, it still has certain limitations. For instance, it does not incorporate subjective weights or consider fuzzy semantic information provided by experts. Future studies may explore expanding the application of the proposed approach to other relevant MCDM problems, such as the selection of green building projects, the training of green building professionals, and the effective management of resource utilization. Moreover, incorporating fuzzy semantic information or integrating subjective weight determination methods—such as the AHP—into the evaluation process, along with exploring alternative decision-making techniques such as weighted aggregated sum product assessment (WASPAS), TOPSIS, or

VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR), may enhance both the analytical depth and practical applicability of the proposed method.

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