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A New Approach to the Viable Ranking of Zero-Carbon Construction Materials with Generalized Fuzzy Information

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Abstract: This paper aims to put forward an integrated decision approach, with generalized fuzzy information for the viable selection of zero- and low-carbon materials for construction. In countries such as India, the construction sector accounts for high pollution levels and high carbon emissions. To restore sustainability and eco-friendliness, the adoption of low-carbon materials for construction is essential and, owing to the multiple attributes associated with the selection, the problem is viewed as a multi-criteria decision-making problem. Earlier studies on material selection have faced certain issues, such as the following: (i) the modeling of uncertainty is an ordeal task; (ii) the flexibility given to experts during preference elicitation is lacking; (iii) the interactions among the criteria are not well captured; and (iv) a consideration of the criteria type is crucial for ranking. To alleviate these issues, the primary objective of this paper was to develop an integrated framework, with decision approaches for material selection in the construction sector that promote sustainability. To this end, generalized fuzzy information (GFI) was adopted as the preference style as it is both flexible and has the ability to model uncertainty from the following three dimensions: membership, non-membership, and hesitancy grades. Furthermore, the CRITIC approach was extended to the GFI context for calculating criteria weights objectively, by effectively capturing criteria interactions. Furthermore, the COPRAS technique was put forward with the GFI rating for ranking zero- and low-carbon construction materials, based on diverse attributes. The usefulness of the framework was demonstrated via a case example from India and the results showed that the design cost, the financial risk, safety, water pollution, and land contamination were the top five criteria, with blended cement, mud bricks, and bamboo as the top three material alternatives for zero- and low-carbon construction. Finally, a sensitivity analysis and a comparison with other methods revealed the theoretical positives of this framework's robustness and consistency–but it also revealed some limitations of the proposed framework.

Keywords: complex proportional assessment; generalized fuzzy set; low-carbon materials; sustainable construction; COPRAS; CRITIC

1. Introduction

Construction is a very important industry in any developing country. In India, the gross domestic product from construction was approximately INR 2240.16 billion (EUR

27.77 billion) between 2011 and 2021 (www.tradingeconomics.com, accessed on 10 February 2022). It is estimated to be approximately 78% of the gross capital formation. With this strength comes the issue of pollution within the country. As it may be noted, India is ranked third out of 106 countries in terms of pollution (www.iqair.com, accessed on 10 February 2022). Indian cities, such as Ghaziabad, Bulandshahr, Bisrakh, and Bhiwadi, rank within the top ten in terms of pollution and such inferences clearly throw light upon the urgent need for the sustainable growth of the nation. In a recent report by Bold Business, it was found that approximately 25% to 40% of the world's pollution comes from construction, and in India construction accounts for 59% of the pollution, which causes air-borne diseases and affects the lives of the people within the nation [1].

Although there are negative impacts from the construction activities within the country, the industry is a powerful driving force of the economy. Therefore, for developing countries, such as India, it is important to strike a balance between the economy and sustainability, hence, sustainable construction seems to be an essential option, as it will not hinder the growth of the nation and it will keep the balance of the ecosystem [2,3]. Sustainability is the concept of "meeting the present needs without impeding the needs of future generation". With a strong notion, the nation committed to reducing their significant carbon trace by 2030, in the Paris Accord [4]. As part of the sustainability mission in the construction domain, the usage of green materials or materials with low- or zero-carbon is a useful and effective idea [5]. Because of the present ecological theme in construction, which strongly supports the usage of sustainable materials for construction, many materials, such as geopolymers, blended cement, fly ash, straw bale, and bamboo, are gaining much attention [6].

Motivation and Contributions

Along with the advent of such materials, there also comes confusion in choosing the proper materials for the construction process. To further add to the confusion, there are many attributes associated with these materials in terms of social, environmental, and economic categories. Typically, this is seen as a multi-attribute decision problem (MADP). Rahim et al. [7], Emovon and Oghenenyerovwho [8], and Zindani et al. [9] provided interesting reviews that suggest the following: (i) the construction sector contributes significantly towards the nation's growth; (ii) material selection with a sustainability and low carbon emissions focus is gaining attention in the recent times; (iii) decision-making approaches, such as the analytical hierarchy process and simple additive weights, are popular for the material selection and application; and (iv) fuzzy sets and its variants are a commonly used preference style for rating alternative materials and criteria, as they can handle uncertainty flexibly. Some challenges that the authors encountered in the extant material selection models were as follows: (i) uncertainties are not effectively modeled with the restrictions placed on experts regarding preference elicitation, thereby affecting their freedom to express their views and opinions on a specific decision entity; (ii) the use of the generalized orthopair structure as rating information is widely unexplored, which affects the notion of sharing membership and non-membership grades; (iii) the hesitation of experts during rating is not captured effectively, which could intuitively aid in the rational estimation of entity values; (iv) owing to the implicit nature of trade-offs in such decision problems, criteria interaction is inevitable and capturing such interactions is crucial for the rational weight estimation that is lacking in the extant models; and (v) finally, such problems have criteria from both benefit and non-benefit types that must be effectively reflected in the formulation of the ranking of alternative materials by presenting complex proportional determination from different angles.

Motivated by these challenges and to tackle the issue, the following contributions have been highlighted:

- The generalized fuzzy structure (GFS) [10] was adopted in this study for the decision process, which can effectively represent uncertainty in three dimensions–such as the

degree of truthfulness, the degree of falsity, and the degree of hesitation. Besides, the structure can flexibly allow experts to share their preference by increasing or shrinking the window size of preference articulation. It may also be noted that the orthopair structure allows the mitigation of subjective randomness during the decision process.
- Criteria importance–through the inter-criteria correlation (CRITIC) technique [11], which comes under the objective weight calculation category–was extended to the GFS for the methodical determination of criteria weights. As claimed by Kao [12], it is clear that the estimation of weights by using a method reduces biases and inaccuracies, which motivated the authors to propose a stepwise procedure for weight calculation. Besides, the claim from Kao [12] towards the variability in the preference distribution mimics the hesitation of the experts, which is also considered in the CRITIC approach and supports the rational calculation of the weights of the criteria.
- Furthermore, the popular complex proportional assessment (COPRAS) technique was extended to the GFS for ranking zero- and low-carbon materials, which could support the construction industry in expediting their sustainability goals.
- Finally, a real case example has been demonstrated to illustrate the usefulness of the integrated model and a comparative study, from both the theoretical and numerical perspectives, is presented to realize both the superiority and the limitations of the model.

In this study, an integrated decision approach was attempted for the rational selection of zero- and low-carbon materials for the construction business. The proposed model intends to reduce human intervention by presenting methods for the systematic calculation of entities. Some of the rationale behind these methods (in the study) is provided below, as follows:

- The GFS [10] is a generalized structure for preference elicitation that mitigates subjective randomness and provides a flexible window for sharing the degree of preference and the degree of non-preference. In the GFS, an adjustable factor (q) is considered and is used to expand or shrink the rating window, allowing experts to flexibly share their views.
- Moreover, the CRITIC technique [11] is an objective weight-calculation approach that not only allows the methodical estimation of weights, but also captures the interaction among criteria and the variability in the preference distribution, which models the hesitation of experts during preference articulation. In this way, it can be intuitively inferred that a criterion with a high interaction with other criteria and a higher variability in the distribution will have a high importance or weight. This indicates that the criterion contains potential information or semantics that are essential or useful for the decision process.
- COPRAS [13] is a popular and powerful ranking technique that effectively considers the nature of the criteria during the ordering of alternatives. Furthermore, the COPRAS method offers ranking from different angles and considers the complex proportionality of the opinions in its formulation of ranking alternatives [14].

The main objective of this research was to develop an integrated decision approach by considering GFI as the preferred style for the rational selection of zero- and low-carbon materials, by considering diverse criteria for evaluation by different experts. Based on the identified challenges, the authors were motivated to propose contributions that aimed to alleviate the challenges. Towards this end, the CRITIC and COPRAS approaches were combined and used as an approach for decision making under the GFI context, with the aim of properly capturing the criteria interactions and the types of criteria.

The rest of the article is structured as follows: Section 2 reviews the literature pertaining to CRITIC, COPRAS, and material selection models. Later, the methodology is explained in detail in Section 3, where the formulae and the implementation steps are provided for the developed framework. A real case example, along with a comparative study is provided in Section 4, which aims to showcase the practical use and the pros and cons of the model. Finally, in Section 5, a conclusion and future research directions are given.

2. Literature Review

In this section, the authors present existing works from the method and application perspectives.

2.1. CRITIC Technique

Weight calculation is a key step in the decision-making process. Generally, weights are calculated by using apriori knowledge (partial) or no prior knowledge. In the former, experts assess the importance of a criterion or criteria in the form of inequality constraints. In the latter, such information is not available and in practical situations the latter context is more common, owing to external factors, such as time limitations, a lack of expertise, pressure, hesitation, and so on [12].

CRITIC [11] is one such objective weight calculation technique, which comes under the latter category. Inspired by its simplicity and its ability to capture interactions among criteria, CRITIC was used by researchers for weight assessment. Rostamzadeh et al. [15] used a hybrid CRITIC-TOPSIS method in the risk assessments of sustainable supply chains, for the effective management of businesses. Babatunde and Ighravwe [16] used a hybrid fuzzy decision model of CRITIC-TOPSIS for a renewable energy system evaluation, with the help of technology and economic factors. Tuş and Aytaç Adalı [17] put forward a hybrid model using CRITIC-WASPAS for software evaluation that manages attendance and time with fuzzy data. Peng et al. [18] ranked 5G industries by adopting an integrated Pythagorean fuzzy framework with CRITIC-CoCoSo, which utilized the newly proposed score function in its formulation. Rani et al. [19] developed a model with single-valued Neutrosophic numbers for food waste treatment method evaluation, by adopting a hybrid method using CRITIC-MULTIMOORA approaches. Wu et al. [20] developed an improved CRITIC and cloud model for safety assessment in urban rail transit applications with uncertain preference information. Žižović et al. [21] developed a novel extension to the CRITIC technique by changing the aggregation and normalization form for the rational calculation of the weights of entities in an objective fashion. Peng and Huang [22] developed a CRITIC-CoCoSo approach with fuzzy data for assessing risk in the financial domain to aid business growth within the sectors. Saraji et al. [23] recently developed an integrated framework that extends CRITIC-COPRAS to Fermatean fuzzy data for ranking challenges that impede the adoption of Industry 4.0, for achieving sustainable digital transformation. Recently, Puška et al. [24] presented a market assessment within Serbia for the pear varieties from farms by adopting a fuzzy-based CRITIC and a distance-based ranking technique. Wang et al. [25] prepared an integrated framework with CRITIC and grey relational projection for hospital evaluation under the probabilistic variant of uncertain linguistic data. Kahraman et al. [26] developed a spherical fuzzy-based CRITIC procedure for ranking criteria associated with supplier selection. Wu et al. [27] developed a multidimensional cloud model with a CRITIC technique for assessing the quality of eutrophic water. Lu et al. [28] put forward a CRITIC-entropy approach with a GRA-TOPSIS combination for ranking agricultural machinery to encourage better farming practices.

2.2. COPRAS Method

Zavadskas et al. [13] gave the inception to the popular ranking method, COPRAS, which considers the nature of criteria and complex proportions to determine the ranks of options. Zavadskas and Antucheviciene [29] utilized the COPRAS method for assessing building redevelopment alternatives with uncertain information. Following its inception, many researchers actively adopted the method for solving different decision problems [30]. Some of the diverse decision applications and areas in which COPRAS is effectively used are as follows: risk analysis [31–33], supplier selection [34,35], ecofriendly aspects [36–39], and the health domain [40], etc.

In recent times, the popularity of the COPRAS method has increased, owing to its ease and elegance. Alinezhad et al. [41] prepared an interesting discussion on COPRAS and showcased its importance and usefulness in diverse applications. Tolga et al. [42] adopted fuzzy COPRAS for prioritizing innovative projects within the air cargo sector with fuzzy data. Sivagami et al. [43] put forward a new probabilistic linguistic framework using the COPRAS method for cloud vendor selection, to manage IT services. Ghose et al. [44] performed material selection for solar vehicles by considering fuzzy data and the COPRAS method. Krishankumar et al. [45] prepared an integrated model with mathematical programming and COPRAS for clean energy selection, by using q-rung orthopair data. Roy et al. [46] evaluated hotels by acquiring data from the web and adopting the COPRAS method to rank hotels under uncertain preference information. Darko and Liang [47] put forward an integrated decision approach with the Maclaurin mean aggregation function and COPRAS, under a dual hesitant context, for evaluating mobile payment platforms. Rani et al. [48] ranked sustainable suppliers by presenting an integrated SWARA-COPRAS method, with hesitant fuzzy data. Roozbahani et al. [49] prepared a framework with fuzzy and grey COPRAS for planning inter-basin water transfers, by considering the case of the Iranian plateau. Aydin [50] evaluated foreign deposit banks by considering uncertain information and the COPRAS method. Mercangzo et al. [51] developed a time period based on COPRAS for assessing the performance index of logistics. Alkan and Albayrak [52] developed the fuzzy-based decision framework for clean energy evaluation within Turkey by extending entropy, COPRAS, and MULTIMOORA approaches. Pamučar and Savin [53] prepared a hybrid model with BWM and COPRAS for off-road vehicle selection to promote passenger transportation. Kumari and Mishra [54] selected green suppliers based on sustainable criteria, under an intuitionistic fuzzy context by extending the COPRAS approach. Shaikh et al. [55] presented fuzzy COPRAS in selecting suitable materials for enhancing braking systems in the automotive sector. Krishankumar et al. [56] selected green suppliers for the purchase of raw materials by considering sustainable criteria and an integrated model with double hierarchy information and the COPRAS method. Nadhira and Dachyar [57] put forward a DEMATEL-, ANP-, and COPRAS-based hybrid framework for factor analysis selection to set up an IoT application. Goswami and Mitra [58] evaluated mobile phones by developing an AHP-COPRAS integrated decision approach with fuzzy data. Lu et al. [59] developed a framework, under a picture fuzzy set for green supplier selection by presenting the COPRAS method. Hezer et al. [60] performed a comparative study of decision methods, such as TOPSIS, COPRAS, and VIKOR, towards the assessment of regional safety measures during the COVID-19 outbreak. Narayanamoorthy et al. [61] prepared an integrated DEMATEL-COPRAS framework for choosing a suitable alternative fuel for sustainable processes. Balali et al. [62] evaluated the risk to human resource, associated with the natural gas supply chain in Shiraz, by presenting a framework with ANP-COPRAS. Hasheminezhad et al. [63] put forward a framework with DEMATEL and COPRAS in the fuzzy context for prioritizing the risk involved in the collision of two passenger trains. Saraji et al. [64] gave a hybrid framework under the Pythagorean fuzzy context by extending the SWARA-CRITIC-COPRAS approaches and evaluating the challenges that affect business intelligence innovations. Wei et al. [65] put forward a new extension to the COPRAS method under a single-valued, neutrosophic, 2-tuple linguistic environment for assessing construction projects' safety aspects. Rajareega and Vimala [66] presented new arithmetic operations with the complex variants of orthopair sets to improve the theoretical foundation and extended the COPRAS method for equipment selection. Thakur et al. [67] developed a new entropy measure and extended COPRAS under the fuzzy context for hospital evaluation. Varatharajulu et al. [68] evaluated the drilling parameters of AZ91 (magnetism) by adopting the COPRAS and TOPSIS methods. Nweze et al. [69] analyzed the properties of mild steel weld for improving performance by adopting the integrated COPRAS-ARAS method.

Jaferzadeh Ghoushchi et al. [70] put forward an integrated BWM-COPRAS framework for health and safety and environmental risk assessment. Guner et al. [71] utilized the spherical fuzzy set to put forward a model with the Hamacher function, AHP, and COPRAS methods for group decision making. Masoomi et al. [72] selected renewable energy suppliers for effective sustainability strategically, by combining the BWM, WASPAS, and COPRAS methods under the fuzzy context. Mishra et al. [73] performed a selection of a desalination technology to support demand by extending the COPRAS method to an interval-valued, hesitant, Fermetean fuzzy environment. Bahrami et al. [74] adopted BWM with COPRAS for the better modeling of the prospectivity of minerals from the spatial context. Ramana et al. [75] prepared a nonlinear, fuzzy-based decision framework for prioritizing the challenges that impede sustainability adoption in industries, by proposing a framework with a variance measure and COPRAS. Xiang et al. [76] developed a combined approach, using SWARA and COPRAS with fuzzy preference information to assess coal transportation firms. Subba and Shabbiruddin [77] utilized the COPRAS method under a fuzzy context in choosing the right material for phase changing, to improve solar energy. Bathrinath et al. [78] adopted fuzzy COPRAS to rank the factors affecting sustainability in snip ports. Omerali and Kaya [79] utilized a spherical fuzzy set and the COPRAS method for the rational selection of augmented reality applications. Kusakci et al. [80] made an assessment of metropolitan cities within Turkey for sustainability aspects, by adopting the AHP and COPRAS method, under an interval-valued, type-2 fuzzy context.

2.3. Material Selection with Decision Approaches

Many researchers applied decision algorithms and models for construction material selection. The main interesting contributions are as follows: Sarpong-Nsiah et al. [81] presented a multi-criteria decision approach to define the best rooftop material for a house; Chama et al. [82] offered a model to identify the finest pallet material of construction (MOC), as perceived by the end consumer, by means of a multi-criteria technique; Obradović and Pamučar [83] presented a new approach, based on fuzzy logic, to support in the decision-making process for the selection of building materials; Haruna et al. [84] used an analytical network process (ANP) to assess the real strategy for materials' effects on the environment; Aghazadeh and Yildirim [85] identified the main principles in the material selection procedure from the perspective of sustainable development; Rajak et al. [86] proposed to apply the VIKOR method to support civil engineers in their choice of sustainable construction materials; Churi and Biswas [87] used an AHP method for the selection of plastering material for a residential building; Maghsoodi et al. [88] approached the selection of the optimal cement material problem using a hybrid decision-making method, based on the step-wise weight assessment ratio analysis (SWARA) and the combinative distance-based assessment (CODAS) models; Roy et al. [89] proposed to extend the CODAS method with interval-valued intuitionistic fuzzy numbers for brick selection in sustainable building design; Czarnigowska et al. [90] proposed a linear programming approach for optimizing the provision of construction materials; Cengiz et al. [91] offered a new approach to suppliers' selection of wall and roofing materials, using an ANP method; Govindan et al. [92], using a hybrid, multi-criteria method and a set of sustainable indicators, proposed to evaluate the finest construction material. Balali et al. [93] applied the PROMETHEE method to the selection of materials and building techniques for the Kashkhan bridge, in Iran; Safa et al. [94] developed an integrated construction materials management (ICMM) model through implementation on the TOPSIS (technique for order preference by similarity to ideal solution); Jiang et al. [95] proposed to support the choice of various wireless technologies for tracking construction materials, using fuzzy decision making; Zavadskas et al. [96] and Zavadskas et al. [97] wrote pioneer papers regarding the use of the decision-making methods in the choice of building materials; Flórez et al. [98] explored the impact of sustainability in an optimization model that can help decision makers to select materials; Jadid and Badrah [99] implemented a decision support system for materials information management for projects under construction by owners; Sefair et al. [100] offered a multiple-criteria decision method to rank candidate materials in building construction, on the basis of their environmental impact, design, and cost; Littidej et al. [101] applied an integrated multi-objective decision analysis (MODA) and a GIS method to choose the possible sites for building material delivery centers (DCs) in a municipality of Thailand; Primova et al. [102] suggested an approach for optimizing the choice of construction material using nonlinear regression equations; Mathiyazhagan et al. [103] selected materials on the basis of a sustainability concept using best–worst methodology (BWM) and a fuzzy TOPSIS approach; Krivogina et al. [104] proposed a multi-criteria approach for the optimal control of the production of building materials. The applications of crisp and fuzzy multiple-criteria decision-making methods in construction, including the domain of building material selection, were reviewed by Wen et al. [105].

2.4. Research Insights

From the review presented above, the following inferences can be drawn: (i) material selection with a green focus is an urgent issue to be tackled in the construction business, to effectively reduce environmental pollution; (ii) CRITIC is an attractive approach for methodically determining objective weights; and (iii) COPRAS is a popular and effective approach for ranking alternatives by properly considering the nature of the criteria. These inferences have driven the authors to propose an integrated decision framework for rational material selection that would reduce environmental hazards and improve green habits, creating a sustainable construction business.

3. Research Methodology

This section presents notions about the proposed framework, which uses integrated approaches to decision making with a GFS.

3.1. Preliminaries

Below, some elementary notions about the q-ROFSs are discussed.

Definition 1 [10]. *Let $\Xi = \{z_1, z_2, \ldots, z_n\}$ be a finite discourse set. A q-ROFS 'M' in Ξ is defined by $M = \{(z_i, \mu_M(z_i), \nu_M(z_i)) | z_i \in \Xi\}$.*

Here, μ_M and ν_M signify the BD and NBD of $z_i \in \Xi$, respectively, $\mu_M(z_i) \in [0,1]$ $\nu_M(z_i) \in [0,1], 0 \le (\mu_M(z_i))^q + (\nu_M(z_i))^q \le 1$, with $q \ge 1$. The hesitation degree is defined as $\pi_M(z_i) = \sqrt[q]{1 - (\mu_M(z_i))^q - (\nu_M(z_i))^q}, \forall z_i \in \Xi.$. The pair $(\mu_M(z_i), \nu_M(z_i))$ is referred to as a q-ROF number, denoted by $\varphi = (\mu_\varphi, \nu_\varphi)$. For q-ROFNs $\varphi = (\mu_\varphi, \nu_\varphi)$, $\varphi_1 = (\mu_{\varphi_1}, \nu_{\varphi_1})$ and $\varphi_2 = (\mu_{\varphi_2}, \nu_{\varphi_2})$, the operations can be represented as

$$\varphi^c = (\nu_\varphi, \mu_\varphi),$$

$$\varphi_1 \oplus \varphi_2 = \left(\sqrt[q]{\mu_{\varphi_1}^q + \mu_{\varphi_2}^q - \mu_{\varphi_1}^q \mu_{\varphi_2}^q}, \nu_{\varphi_1}\nu_{\varphi_2}\right),$$

$$\varphi_1 \otimes \varphi_2 = \left(\mu_{\varphi_1}\mu_{\varphi_2}, \sqrt[q]{\nu_{\varphi_1}^q + \nu_{\varphi_2}^q - \nu_{\varphi_1}^q \nu_{\varphi_2}^q}\right),$$

$$\varsigma\varphi = \left(\sqrt[q]{1 - (1 - \mu_\varphi^q)^\varsigma}, \nu_\varphi^\varsigma\right), \varsigma > 0,$$

$$\varphi^\varsigma = \left(\mu_\varphi^\varsigma, \sqrt[q]{1 - (1 - \nu_\varphi^q)^\varsigma}\right), \varsigma > 0.$$

Definition 2 [106]. *Let* $\varphi = (\mu_\varphi, \nu_\varphi)$ *be a q-ROFN. Then, score and accuracy functions of* φ *are presented as*

$$\mathbb{S}(\varphi) = \frac{1}{2}\left(\left(\mu_\varphi^q - \nu_\varphi^q\right) + 1\right) \text{ and } \hbar(\varphi) = \mu_\varphi^q + \nu_\varphi^q. \tag{1}$$

For any q-ROFNs $\varphi_1 = (\mu_{\varphi_1}, \nu_{\varphi_1})$ and $\varphi_2 = (\mu_{\varphi_2}, \nu_{\varphi_2})$:

(i) If $\mathbb{S}(\varphi_1) > \mathbb{S}(\varphi_2)$, then $\varphi_1 > \varphi_2$,
(ii) If $\mathbb{S}(\varphi_1) = \mathbb{S}(\varphi_2)$, then
(iii) if $\hbar(\varphi_1) > \hbar(\varphi_2)$, then $\varphi_1 < \varphi_2$,
(iv) if $\hbar(\varphi_1) = \hbar(\varphi_2)$, then $\varphi_1 = \varphi_2$.

Definition 3 [107]. *Let* $\varphi_1 = (\mu_{\varphi_1}, \nu_{\varphi_1})$ *and* $\varphi_2 = (\mu_{\varphi_2}, \nu_{\varphi_2})$ *be the q-ROFNs. The distance measure for* φ_1 *and* φ_2 *is presented as*

$$D(\varphi_1, \varphi_2) = \frac{1}{2}\left(\left|\mu_{\varphi_1}^q - \mu_{\varphi_2}^q\right| + \left|\nu_{\varphi_1}^q - \nu_{\varphi_2}^q\right| + \left|\pi_{\varphi_1}^q - \pi_{\varphi_2}^q\right|\right). \tag{2}$$

3.2. Q-ROF-CRITIC-COPRAS Framework

Zavadskas et al. [13] discussed COPRAS as an effective tool that can offer an optimum result, related to the ideal solution (IS) and the anti-ideal solution (A-IS). For that reason, it can be considered as a flexible MCDM technique. The assessment procedure of the proposed method is given by the following steps:

Step 1: Create a linguistic decision matrix (LDM).

A set of ℓ "decision makers (DMs)" $D = \{d_1, d_2, \ldots, d_\ell\}$ determine the sets of m options $O = \{o_1, o_2, \ldots, o_m\}$ and n criteria $B = \{b_1, b_2, \ldots, b_n\}$, respectively. Let $\mathbb{Z}^{(k)} = \left(\xi_{ij}^{(k)}\right)_{m\times n}, i = 1,2,\ldots,m, j = 1,2,\ldots,n$ be the LDM, suggested by the DMs, where $\xi_{ij}^{(k)}$ mentions the assessment of an alternative oi, with respect to criterion bj, given by kth DM.

Step 2: Estimate the weights of the DMs.

To obtain the weight of kth DM, let $d_k = (\mu_k, \nu_k)$ be a q-ROFN. Now, the weight values are calculated as

$$\varpi_k = \frac{\left(\mu_k^q + \pi_k^q \times \left(\frac{\mu_k^q}{\mu_k^q + \nu_k^q}\right)\right)}{\sum_{k=1}^{\ell}\left(\mu_k^q + \pi_k^q \times \left(\frac{\mu_k^q}{\mu_k^q + \nu_k^q}\right)\right)}, k = 1(1)\ell. \tag{3}$$

Here, $\varpi_k \geq 0$ and $\sum_{k=1}^{\ell} \varpi_k = 1$.

Step 3: Aggregate all the q-ROF-DMs.

To create the q-ROF-aggregated decision matrix (q-ROF-ADM), a q-ROF weighted averaging (q-ROFWA) operator is used and then $\mathbb{Z} = (\xi_{ij})_{m\times n}$, where

$$\xi_{ij} = q - ROFWA_{\varpi}\left(\xi_{ij}^{(1)}, \xi_{ij}^{(2)}, \ldots, \xi_{ij}^{(\ell)}\right) = \left(\sqrt[q]{1 - \prod_{k=1}^{\ell}\left(1 - \mu_k^q\right)^{\varpi_k}}, \prod_{k=1}^{\ell}(\nu_k)^{\varpi_k}\right) \tag{4}$$

Step 4: Use the CRITIC tool for the estimation of criteria weights.

Let $w = (w_1, w_2, \ldots, w_n)^T$ be the criteria weight, such that $\omega_j \in [0,1]$ and $\sum_{j=1}^{n} \omega_j = 1$. In this line, the intensity contrast of the criteria is estimated by the "standard deviation (SD)", and the conflict among the criteria is computed by the "correlation coefficient (CRC)". The steps for CRITIC on q-ROFSs are given by the following:

Step 4a: The estimation of the score matrix $S = (\xi_{ij})_{m\times n}, i = 1(1)m, j = 1(1)n$, where

$$\xi_{ij} = \frac{1}{2}\left(\left(\mu_{ij}^q - \nu_{ij}^q\right) + 1\right). \tag{5}$$

Step 4b: Construct the standard q-ROF-matrix $\tilde{S} = \left(\tilde{\xi}_{ij}\right)_{m\times n}$

$$\tilde{\xi}_{ij} = \begin{cases} \dfrac{\xi_{ij} - \xi_j^-}{\xi_j^+ - \xi_j^-}, j \in s_b \\ \dfrac{\xi_j^+ - \xi_{ij}}{\xi_j^+ - \xi_j^-}, j \in s_n \end{cases} \tag{6}$$

wherein $\xi_j^+ = \max_i \xi_{ij}$ and $\xi_j^- = \min_i \xi_{ij}$.

Step 4c: The SDs for each criterion in the given expression:

$$\sigma_j = \sqrt{\frac{\sum_{i=1}^m \left(\tilde{\xi}_{ij} - \bar{\tilde{\xi}}_j\right)^2}{m}}, \text{ wherein } \bar{\tilde{\xi}}_j = \sum_{i=1}^m \frac{\tilde{\xi}_{ij}}{m}. \tag{7}$$

Step 4d: Assess the CRC between the criteria pairs:

$$r_{jt} = \frac{\sum_{i=1}^m \left(\tilde{\xi}_{ij} - \bar{\tilde{\xi}}_j\right)\left(\tilde{\xi}_{it} - \bar{\tilde{\xi}}_t\right)}{\sqrt{\sum_{i=1}^m \left(\tilde{\xi}_{ij} - \bar{\tilde{\xi}}_j\right)^2 \sum_{i=1}^m \left(\tilde{\xi}_{it} - \bar{\tilde{\xi}}_t\right)^2}}. \tag{8}$$

Step 4e: Estimate the quantity of information for each criterion as

$$c_j = \sigma_j \sum_{t=1}^n \left(1 - r_{jt}\right). \tag{9}$$

Step 4f: The objective weights of the criteria are obtained by

$$w_j = \frac{c_j}{\sum_{j=1}^n c_j}. \tag{10}$$

Step 5: The sum of the cost- and benefit-type criteria ratings.

Each option is estimated with the addition of rating (τ_i) for the benefit-type criterion and the assessment rating (ι_i) for the cost-type criterion. Let $\Omega = \{1,2,\ldots,l\}$ be the criterion, then the benefit-type criterion-based rating (τ_i) for each alternative is given as

$$\tau_i = \sum_{j=1}^l w_j \xi_{ij}, \forall i. \tag{11}$$

Let $\mho = \{l+1, l+2, \ldots, n\}$ be the cost-type criteria set, then the cost-type criterion-based rating (ι_i) for each option is described as

$$\iota_i = \sum_{j=l+1}^n w_j \xi_{ij}, \forall i. \tag{12}$$

In Equations (11) and (12), l is the number of the benefit-type criteria, n is the whole criteria and w_j is the weight.

Step 6: Computation of the relative degree of alternatives.

To evaluate the relative degree γ_i of i^{th} option, the procedure is as follows:

$$\gamma_i = \varphi(\tau_i)\,\mathbb{S}(\tau_i) + (1-\varphi)\frac{\min_i \mathbb{S}(\iota_i)\sum_{i=1}^m \mathbb{S}(\iota_i)}{\mathbb{S}(\iota_i)\sum_{i=1}^m \frac{\min_i \mathbb{S}(\iota_i)}{\mathbb{S}(\iota_i)}}, \forall i, \tag{13}$$

wherein $\mathbb{S}(\tau_i)$ and $\mathbb{S}(\iota_i)$ present the score degrees of τ_i and ι_i, respectively. Besides, the parameter φ denotes the strategy value of the DE in a unit interval.

Another form of Equation (13) is presented as

$$\gamma_i = \varphi\mathbb{S}(\tau_i) + (1-\varphi)\frac{\sum_{i=1}^m \mathbb{S}(\iota_i)}{\mathbb{S}(\iota_i)\sum_{i=1}^m \frac{1}{\mathbb{S}(\iota_i)}}, \forall i. \tag{14}$$

Step 7: Prioritize the alternatives.

The maximum relative degree of an alternative is described as the higher priority. Hence, the optimum option is obtained as follows:

$$\gamma_{max} = \max_i \gamma_i, i = 1,2,\ldots,m. \quad (15)$$

Step 8: Evaluate the utility degree.

Now, the process for the assessment of the degree of utility of the alternatives is defined by

$$\delta_i = \frac{\gamma_i}{\gamma_{max}} \times 100\%, \forall i. \quad (16)$$

Here, γ_i and γ_{max} are given by Equations (14)–(15).

The figures presented in Figure 1 show the proposed integrated model with qROF settings that initially acquire Likert scale rating data, which are converted to qROF data, based on the tabular form.

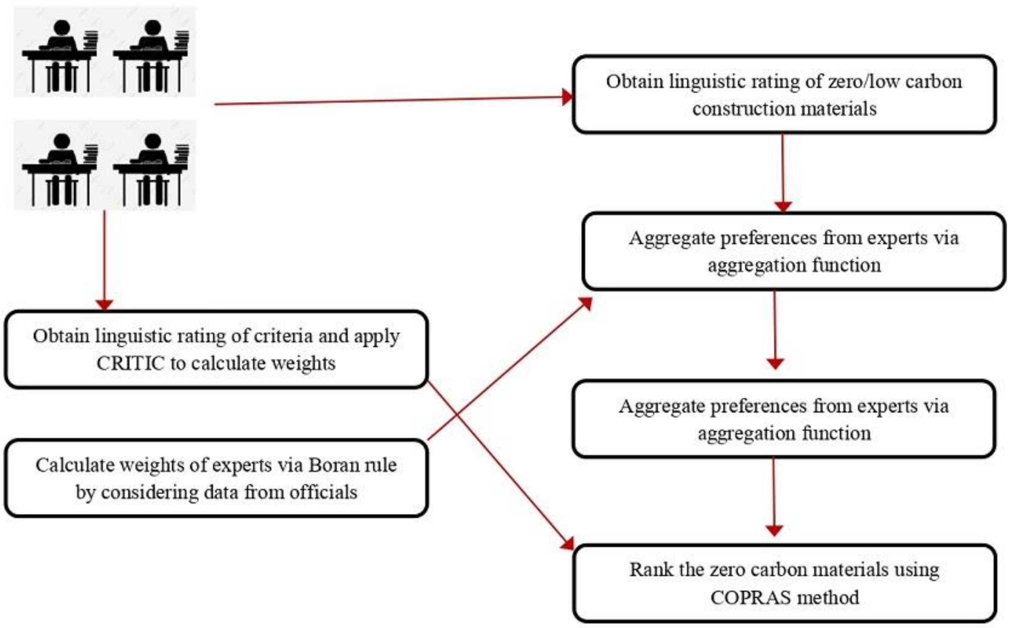

Figure 1. Integrated qROF decision framework for zero- and low-carbon material selection.

The importance of the experts was methodically determined, based on the data from the officials (who constituted the panel) and the Boran rule. The CRITIC method was put forward for determining the weights of the criteria by efficiently capturing the interrelationship among the criteria. By using the importance of the experts, the preferences were aggregated, and these were used, along with the weights of the criteria for determining the ordering of materials via the qROF-COPRAS method. From a mathematical viewpoint, the a matrices of $b \times c$ order were considered along with a criteria weight calculation matrix of $a \times c$ order. The experts' importance was calculated and a vector of $1 \times a$ was obtained. Later, an aggregated matrix of $b \times c$ was obtained via the aggregation function, by utilizing the preference data and the calculated experts' weights. By using the CRITIC method, $1 \times c$ was obtained, which was used along with an aggregated matrix for ranking the materials via the COPRAS method, which yielded a vector of $1 \times b$.

4. Real Case Example

This section puts forward a case example to demonstrate the usefulness of the proposed model. In developing countries, such as India, the construction industry contributed approximately INR 2250.13 billion (EUR 27.89 billion) between 2011–2021, as per the claim from tradingeconomics.com (accessed on 15 April 2022). Evidently, the market is high and there is great scope for development. However, with this abundant opportunity, there also comes the issue of pollution. As discussed earlier, India is affected by this problem of pollution and is ranked below average in terms of eco-health and safety. In order to boost its ranking and attain the global safety threshold, India has made strong commitments; one such commitment is the resolution of India to reduce its carbon footprint by 35–38%, made in the Paris Accord [4]. To achieve this goal, the nation plans to adopt sustainable habits and green practices in developmental and daily activities. The adoption of six sigma and lean concepts are crucial in such industries as they not only manage pollution, but also aid in profit making [108].

In line with this train of thought, an academic institution plans to construct a building for research activities, setting up research centers with sophisticated infrastructure for faculties and students to become actively involved in research and development. The civil department of the institute prepared a detailed proposal for the building, keeping in mind the core sustainability aspects, which would adhere to the green policies of the nation and would target an ecofriendly design and construction of the building, without causing damage to the ecosystem. One essential step towards this goal is the selection of materials that follow green or sustainable paradigms. The institution, after scrutinizing the proposal, decided to opt for green building constructions by utilizing low-carbon materials for its construction. The officials of the institute constitute a panel of four experts, who participated in the decision problems for the rational selection of low-carbon materials. The four experts are well qualified and have adequate expertise in the construction domain. A senior professor from the sustainable construction department, a research scientist from the material science field, a construction engineer, and finance and audit personnel, form the expert panel. First, an initial list of low-carbon materials were gathered, these are then revised based on their need. The following five low-carbon materials were chosen for the present study: blended cement, geopolymers, bamboo, grapheme-induced concrete, and mud bricks. For brevity, we have denoted them as O_1, O_2, O_3, O_4, and O_5. Furthermore, the panel prepared a list of criteria, upon which these materials would be rated. Based on the voting principle, 13 criteria were finalized. The following criteria were considered for this study: safety, opportunities for jobs, culture and heritage, stakeholder satisfaction, air pollution, eco-friendliness, water pollution, waste generation, soil contamination, labor costs, maintenance costs, design costs, and socio-economic risks. Pollutions, costs, and risks are of cost-type criteria and the others are benefit-type criteria. The authors have denoted them as b_1, b_2,…, b_{13}. The four experts are denoted as d_1, d_2, d_3, and d_4, respectively. The rating was done qualitatively, by using linguistic scales.

Steps 1–2: Table 1 depicts the significance of the DEs and the criteria in the form of LVs, which are then converted into q-ROFNs. Table 2 presents the DEs weight, based on Table 1 and Equation (3). Table 3 describes the importance of the DEs in evaluating the options and the assessments of the options, concerning each attribute.

Table 1. Performance degree of alternatives and criteria in the form of LVs.

LVs	q-ROFNs
Absolutely high (AH)/Extremely significant (ES)	(0.95, 0.20, 0.240)
Very high (VH)/Very significant (VS)	(0.80, 0.35, 0.487)
High (H)/Significant (S)	(0.70, 0.45, 0.554)
Moderate high (MH)/Moderate significant (MS)	(0.60, 0.55, 0.581)
Moderate (M)/Average (A)	(0.50, 0.60, 0.624)
Moderate low (ML)/Moderate insignificant (MI)	(0.40, 0.70, 0.592)
Low (L)/Very insignificant (VI)	(0.30, 0.75, 0.589)

Very low (VL)/Very very insignificant (VVI)	(0.20, 0.85, 0.487)
Absolutely low (AL)/Extremely insignificant (EI)	(0.10, 0.95, 0.296)

Table 2. Weight of Des for evaluation of the alternatives.

DEs	LVs	q-ROFNs	Weights
d_1	Significant (S)	(0.70, 0.45, 0.554)	0.2321
d_2	Very very significant (VVS)	(0.80, 0.35, 0.487)	0.2753
d_3	Very significant (VS)	(0.95, 0.20, 0.240)	0.3143
d_4	Moderate significant (MS)	(0.60, 0.55, 0.581)	0.1783

Table 3. LDM of alternative over different criteria by DEs.

	O_1	O_2	O_3	O_4	O_5
b_1	(ML, MH, L, L)	(H, MH, A, A)	(AL, VL, L, A)	(VL, MH, A, A)	(A, L, L, VL)
b_2	(H, A, VL, MH)	(ML, AL, L, MH)	(L, A, ML, ML)	(ML, VL, AL, ML)	(AL, L, L, MH)
b_3	(MH, AL, ML, AL)	(AL, VL, A, L)	(ML, L, H, VL)	(ML, ML, A, MH)	(MH, L, H, H)
b_4	(MH, ML, AL, A)	(ML, ML, ML, A)	(H, MH, A, H)	(ML, L, L, VL)	(H, AL, A, A)
b_5	(A, L, ML, L)	(A, ML, MH, A)	(VL, MH, VL, MH)	(L, A, H, ML)	(VL, L, ML, ML)
b_6	(ML, A, AL, A)	(ML, VL, VL, MH)	(L, ML, ML, H)	(L, A, ML, ML)	(L, A, VL, L)
b_7	(A, MH, H, A)	(ML, H, A, MH)	(ML, ML, ML, H)	(MH, L, L, L)	(H, VL, VL, MH)
b_8	(AL, L, L, VL)	(ML, MH, L, H)	(H, L, A, ML)	(VL, L, H, A)	(MH, A, H, VL)
b_9	(ML, VL, A, AL)	(AL, L, ML, MH)	(MH, VL, MH, A)	(ML, MH, VL, A)	(AL, L, L, MH)
b_{10}	(VL, ML, MH, L)	(H, ML, VL, ML)	(A, VL, A, ML)	(MH, ML, A, VL)	(A, VL, L, L)
b_{11}	(VL, VL, VL, A)	(A, VL, A, ML)	(H, VL, MH, ML)	(A, ML, A, MH)	(VL, A, VL, ML)
b_{12}	(VL, VL, H, H)	(L, A, ML, L)	(L, L, MH, H)	(AL, MH, A, ML)	(H, VL, MH, A)
b_{13}	(AL, MH, VL, MH)	(MH, MH, ML, MH)	(A, A, AL, AL)	(VL, A, ML, VL)	(A, A, MH, A)

Step 3: The LDM provided by four DEs have been combined by Equation (4) for each option, over diverse criteria of zero-carbon construction material selection into an A-q-ROF-DM $A = (\xi_{ij})_{m\times n}$, and is depicted in Table 4.

Table 4. A-q-ROF-DM for options over different criteria of zero-carbon construction material selection.

	O_1	O_2	O_3	O_4	O_5
b_1	(0.435, 0.678, 0.593)	(0.586, 0.548, 0.597)	(0.322, 0.761, 0.563)	(0.490, 0.635, 0.597)	(0.349, 0.728, 0.590)
b_2	(0.529, 0.617, 0.583)	(0.376, 0.745, 0.551)	(0.413, 0.682, 0.604)	(0.287, 0.813, 0.507)	(0.358, 0.750, 0.556)
b_3	(0.388, 0.760, 0.521)	(0.337, 0.765, 0.549)	(0.498, 0.643, 0.582)	(0.477, 0.639, 0.603)	(0.608, 0.543, 0.580)
b_4	(0.432, 0.709, 0.558)	(0.420, 0.681, 0.600)	(0.622, 0.521, 0.585)	(0.313, 0.755, 0.576)	(0.510, 0.637, 0.578)
b_5	(0.389, 0.697, 0.602)	(0.514, 0.609, 0.604)	(0.449, 0.698, 0.559)	(0.539, 0.593, 0.597)	(0.338, 0.746, 0.573)
b_6	(0.400, 0.718, 0.569)	(0.366, 0.752, 0.548)	(0.466, 0.657, 0.592)	(0.413, 0.682, 0.604)	(0.350, 0.734, 0.582)
b_7	(0.603, 0.535, 0.591)	(0.572, 0.566, 0.594)	(0.481, 0.647, 0.592)	(0.402, 0.698, 0.593)	(0.478, 0.679, 0.557)
b_8	(0.251, 0.810, 0.530)	(0.518, 0.619, 0.590)	(0.512, 0.613, 0.601)	(0.508, 0.632, 0.585)	(0.575, 0.572, 0.585)
b_9	(0.366, 0.743, 0.560)	(0.387, 0.734, 0.558)	(0.514, 0.630, 0.583)	(0.451, 0.677, 0.581)	(0.358, 0.750, 0.556)
b_{10}	(0.439, 0.687, 0.578)	(0.469, 0.672, 0.574)	(0.425, 0.679, 0.599)	(0.470, 0.653, 0.594)	(0.342, 0.737, 0.583)
b_{11}	(0.285, 0.799, 0.530)	(0.425, 0.679, 0.599)	(0.536, 0.618, 0.575)	(0.498, 0.616, 0.610)	(0.352, 0.746, 0.565)
b_{12}	(0.545, 0.621, 0.563)	(0.398, 0.690, 0.604)	(0.515, 0.621, 0.591)	(0.468, 0.670, 0.577)	(0.549, 0.601, 0.581)
b_{13}	(0.442, 0.716, 0.540)	(0.550, 0.593, 0.587)	(0.374, 0.752, 0.542)	(0.374, 0.727, 0.576)	(0.535, 0.584, 0.610)

Step 4: To estimate the criteria weights, the CRITIC tool was used on q-ROFSs. Using Equation (5) and Table 4, firstly we obtained the score-matrix $S = (\xi_{ij})_{p\times q}$. After, we computed the standard q-ROF-matrix $\tilde{S} = (\tilde{\chi}_{ij})_{p\times q}$by Equation (6). By using Equations (7)–(9), the SD, CRC, and quantity of information of each criterion were estimated. The weights of criteria were estimated by using Equation (10) and referred to in Table 5.

Table 5. The standard q-ROF-matrix $\tilde{S} = \left(\tilde{\xi}_{ij}\right)_{m\times n}$, SD, quantity of information, and weight values.

Criteria	O_1	O_2	O_3	O_4	O_5	σ_j	c_j	w_j
b_1	0.397	1.000	0.000	0.602	0.130	0.355	5.325	0.0891
b_2	1.000	0.344	0.595	0.000	0.303	0.334	3.756	0.0628
b_3	0.079	0.000	0.560	0.532	1.000	0.363	4.417	0.0739
b_4	0.264	0.314	1.000	0.000	0.554	0.336	4.018	0.0672
b_5	0.715	0.121	0.588	0.000	1.000	0.373	3.979	0.0666
b_6	0.346	0.000	1.000	0.634	0.072	0.370	4.716	0.0789
b_7	0.000	0.175	0.656	1.000	0.767	0.374	5.041	0.0843
b_8	1.000	0.198	0.198	0.244	0.000	0.346	4.137	0.0692
b_9	0.948	0.849	0.000	0.408	1.000	0.382	4.779	0.0799
b_{10}	0.334	0.116	0.337	0.000	1.000	0.346	3.896	0.0652
b_{11}	1.000	0.401	0.000	0.082	0.731	0.380	4.353	0.0728
b_{12}	0.114	1.000	0.236	0.661	0.000	0.373	5.823	0.0974
b_{13}	0.711	0.000	1.000	0.899	0.014	0.433	5.535	0.0926

Here, Figure 2 indicates the weights of the diverse criteria of zero-carbon construction material selection, with respect to the goal. The design cost (b_{12}) with the weight value 0.0974, have come out to be the most significant criteria of zero- and low-carbon construction material selection. The financial risk (b_{13}) with the weight value 0.0926, was the second most important criteria of zero- and low-carbon construction material selection. Safety (b_1) was in third position (significance), with the value 0.0891. Water pollution (b_7) was placed fourth, with the weight value 0.0843. Soil/land contamination (b_9), with the significance value 0.0799, was the fifth most important criteria of zero- and low-carbon construction material selection. This ranking follows for the other criteria as well, which are also considered crucial criteria of zero- and low-carbon construction material selection.

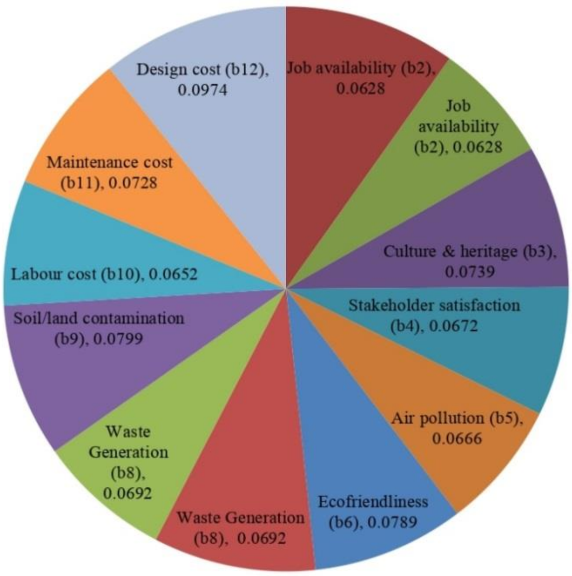

Figure 2. Significance values/weight of the different criteria of zero-carbon construction material selection.

Steps 5–8: In the process of the assessment of the criteria of zero-carbon construction material selection, all risk factors are the maximum type. Using Equations (11)–(16), the values of $\tau_i, \iota_i, \gamma_i$ and δ_i of $O_i(i = 1(1)5)$ were computed over the criteria $b_j(j = 1(1)13)$, and specified in Table 6. As seen in Table 7, the ranking order of the material alternatives is $O_1 \succ O_3 \succ O_5 \succ O_4 \succ O_2$ and, thus, O_1 is the best material, based on the ratings of the different criteria for the zero- and low-carbon construction material selection problem.

Table 6. The outcome of q-ROF-CRITIC-COPRAS model.

Option	$\boldsymbol{\tau_i}$	$\mathbb{S}(\boldsymbol{\tau_i})$	$\boldsymbol{\iota_i}$	$\mathbb{S}(\boldsymbol{\iota_i})$	$\boldsymbol{\gamma_i}$	$\boldsymbol{\delta_i}$	Ranking
O_1	(0.275, 0.874, 0.400)	0.1559	(0.361, 0.792, 0.492)	0.2516	0.2261	100.00	1
O_2	(0.278, 0.869, 0.409)	0.1609	(0.395, 0.758, 0.520)	0.2910	0.2086	92.24	5
O_3	(0.301, 0.854, 0.425)	0.1807	(0.389, 0.768, 0.509)	0.2812	0.2229	98.58	2
O_4	(0.261, 0.873, 0.412)	0.1529	(0.375, 0.771, 0.514)	0.2728	0.2131	94.25	4
O_5	(0.285, 0.864, 0.415)	0.1675	(0.376, 0.775, 0.507)	0.2703	0.2217	98.02	3

4.1. Comparative Discussion

The outcomes of the q-ROF-CRITIC-COPRAS tool are compared with the extant approaches. Towards this end of demonstrating the efficacy and the unique advantages of the introduced method, the q-ROF-TOPSIS [107] and q-ROF-WASPAS [48] methods were used to treat the same problem.

4.1.1. Q-ROF-TOPSIS Approach

Steps 1–4: The same as the aforementioned model.

Step 5: Assess the "q-ROF-ideal solution (q-ROF-IS)" and the "q-ROF-anti-ideal solution (q-ROF-AIS)".

Let ζ^+ and ζ^- present the q-ROF-IS and the q-ROF-AIS, and they are given by

$$\zeta^+ = \left(\mu_\zeta^+, \nu_\zeta^+\right) = \begin{cases} \max\limits_i \mu_{ij}, for\ benefit\ criterion\ b_b \\ \min\limits_i \nu_{ij}, for\ cost\ criterion\ b_n \end{cases} for\ j = 1(1)n, \tag{17}$$

$$\zeta^- = \left(\mu_\zeta^-, \nu_\zeta^-\right) = \begin{cases} \min\limits_i \mu_{ij}, for\ benefit\ criterion\ b_b \\ \max\limits_i \nu_{ij}, for\ cost\ criterion\ b_n \end{cases} for\ j = 1(1)n. \tag{18}$$

Step 6: Obtain the distances of the options from q-ROF-IS and q-ROF-AIS.

From Equation (2), we computed the distances $D(y_i, \zeta^+)$ between the option O_i and q-ROF-IS ζ^+.

$$D(O, \zeta^+) = \frac{1}{2}\sum_{j=1}^{n}\left[w_j\left(\left|\mu_{\xi_{ij}}^q - \left(\mu_\zeta^+\right)^q\right| + \left|\nu_{\xi_{ij}}^q - \left(\nu_\zeta^+\right)^q\right| + \left|\pi_{\xi_{ij}}^q - \left(\pi_\zeta^+\right)^q\right|\right)\right] \tag{19}$$

and the discrimination $D(O_i, \zeta^-)$ between the option O_i and q-ROF-AIS ζ^- was given by

$$D(O_i, \zeta^-) = \frac{1}{2}\sum_{j=1}^{n}\left[w_j\left(\left|\mu_{\xi_{ij}}^q - \left(\mu_\zeta^-\right)^q\right| + \left|\nu_{\xi_{ij}}^q - \left(\nu_\zeta^-\right)^q\right| + \left|\pi_{\xi_{ij}}^q - \left(\pi_\zeta^-\right)^q\right|\right)\right] \tag{20}$$

Step 7: Assess the closeness index (CI).

The CI of each alternative can be calculated as follows:

$$RC(y_i) = \frac{D(O_i, \zeta^-)}{D(O_i, \zeta^+) + D(O_i, \zeta^-)}, \forall i. \tag{21}$$

Step 8: Choose the maximum degree, $RC(O_k)$, among the degrees $RC(O_i)$. This validates that O_k is the optimal choice.

Now, the q-ROF-IS and q-ROF-AIS are obtained by Equations (17)–(18), as follows: ζ^+ = {(0.586, 0.548, 0.597), (0.529, 0.617, 0.583), (0.608, 0.543, 0.580), (0.622, 0.521, 0.585), (0.338, 0.746, 0.573), (0.466, 0.657, 0.592), (0.402, 0.698, 0.593), (0.251, 0.810, 0.530), (0.358, 0.750, 0.556), (0.342, 0.737, 0.583), (0.285, 0.799, 0.530), (0.398, 0.690, 0.604), (0.374, 0.752, 0.542)},

ζ^- ={(0.322, 0.761, 0.563), (0.287, 0.813, 0.507), (0.337, 0.765, 0.549), (0.313, 0.755, 0.576), (0.539, 0.593, 0.597), (0.366, 0.752, 0.548), (0.603, 0.535, 0.591), (0.575, 0.572, 0.585), (0.514, 0.630, 0.583), (0.470, 0.653, 0.594), (0.536, 0.618, 0.575), (0.549, 0.601, 0.581), (0.550, 0.593, 0.587)}.

The outcomes of q-ROF-TOPSIS are presented by Equations (19)–(21) and are depicted in Table 7. Lastly, the ranking of the alternatives was obtained as $O_1 \succ O_5 \succ O_3 \succ O_4 \succ O_2$; therefore, of all the different criteria of zero-carbon construction material selection, the best option is O_1.

Table 7. Prioritization of alternative, with a q-ROF-TOPSIS model

Options	$\boldsymbol{D(O_i, \zeta^+)}$	$\boldsymbol{D(O_i, \zeta^-)}$	$\boldsymbol{RC(O_i)}$	Ranking
O_1	0.103	0.127	0.5540	1
O_2	0.149	0.096	0.3901	5
O_3	0.124	0.116	0.4836	3
O_4	0.146	0.110	0.4296	4
O_5	0.126	0.124	0.4972	2

4.1.2. Q-ROF-WASPAS Model

Steps 1–4: Similar to the aforesaid model.

Step 5: For each option, we estimate the degrees of the “weighted-sum method (WSM)” $C_i^{(1)}$, as follows:

$$\mathrm{C}_{\mathrm{i}}^{(1)} = \sum_{\mathrm{j}=1}^{\mathrm{n}} \mathrm{w}_{\mathrm{j}} \xi_{\mathrm{ij}}. \tag{22}$$

Step 6: For each option, we compute the degrees of the “weighted-product method (WPM)” $C_i^{(2)}$, as follows:

$$C_i^{(2)} = \prod_{j=1}^{n} w_j \xi_{ij}. \tag{23}$$

Step 7: For each option, we obtain the degree of WASPAS measure as

$$C_i = \lambda C_i^{(1)} + (1 - \lambda) C_i^{(2)}, \tag{24}$$

where λ stands for the parameter of the decision mechanism and $\lambda \in [0,1]$.

Step 8: Rank the alternatives according to the decreasing ratings (i.e., score values) of C_i.

Steps 5–8: By applying Equations (22)–(24), the WSM $\left(C_i^{(1)}\right)$, the WPM $\left(C_i^{(2)}\right)$, and the WASPAS (C_i) measures for each option were obtained and are depicted in Table 8. Therefore, the prioritization of the material was assessed as follows: $O_1 \succ O_5 \succ O_3 \succ O_4 \succ O_2$, with O_1 being the best option. On the other hand, the outcomes were slightly different between the developed and the extant models. Therefore, the q-ROF-CRITIC-COPRAS method is more robust and is steadier than the q-ROF-TOPSIS and q-ROF-WASPAS tools and, thus, has wider applicability.

Table 8. Outcomes of q-ROF-WASPAS approach.

Options	WSM		WPM		WASPAS $\boldsymbol{C_i(\lambda)}$	Ranking
	$\boldsymbol{C_i^{(1)}}$	$\mathbb{S}\left(\boldsymbol{C_i^{(1)}}\right)$	$\boldsymbol{C_i^{(2)}}$	$\mathbb{S}\left(\boldsymbol{C_i^{(2)}}\right)$		
O_1	(0.637, 0.499, 0.588)	0.5782	(0.579, 0.570, 0.5831)	0.5054	0.542	1
O_2	(0.589, 0.544, 0.598)	0.5258	(0.546, 0.588, 0.5962)	0.4762	0.501	5
O_3	(0.606, 0.533, 0.590)	0.5417	(0.568, 0.566, 0.5971)	0.5014	0.522	3
O_4	(0.596, 0.533, 0.601)	0.5356	(0.547, 0.580, 0.6040)	0.4811	0.508	4
O_5	(0.616, 0.515, 0.596)	0.5569	(0.561, 0.570, 0.5997)	0.4947	0.526	2

As compared to the above-discussed methods, the q-ROF-CRITIC-COPRAS method is more robust and, thus, has wider applicability. The key benefits of the q-ROF-CRITIC-COPRAS method are as follows (see Figure 3):

- The q-ROFSs can reflect the DE's hesitancy more objectively than other classical extensions of FS. Therefore, the use of the developed q-ROF-CRITIC-COPRAS approach gives a more flexible way to express the uncertainty when evaluating the criteria of zero-carbon construction material selection.
- The CRITIC method is employed to evaluate the objective weights of each criterion in the evaluation of the criteria of zero-carbon construction material selection, which makes the introduced q-ROF-CRITIC-COPRAS method a more reliable, efficient, and sensible tool.
- The proposed q-ROF-CRITIC-COPRAS method can process the information in a more useful and a more suitable way and from different perspectives, such as benefit-type and cost-type criteria.

Based on the rank values from the proposed and extant methods, it was inferred that the ordering was determined as $O_1 \succ O_5 \succ O_3 \succ O_4 \succ O_2$. With obviously different rank values but the same ordering, this indicates the intact nature of the rank orders of zero- and low-carbon materials for construction. Based on the ordering from the different qROF methods, the Spearman correlation was applied, and the consistency coefficients were determined as unity, with respect to the proposed and the other methods. This implies that the model is highly consistent with other extant models in the qROF setting. Figure 4 depicts the coefficients and confidence value when the rank orders of the proposed and extant methods were fed into the Spearman correlation approach.

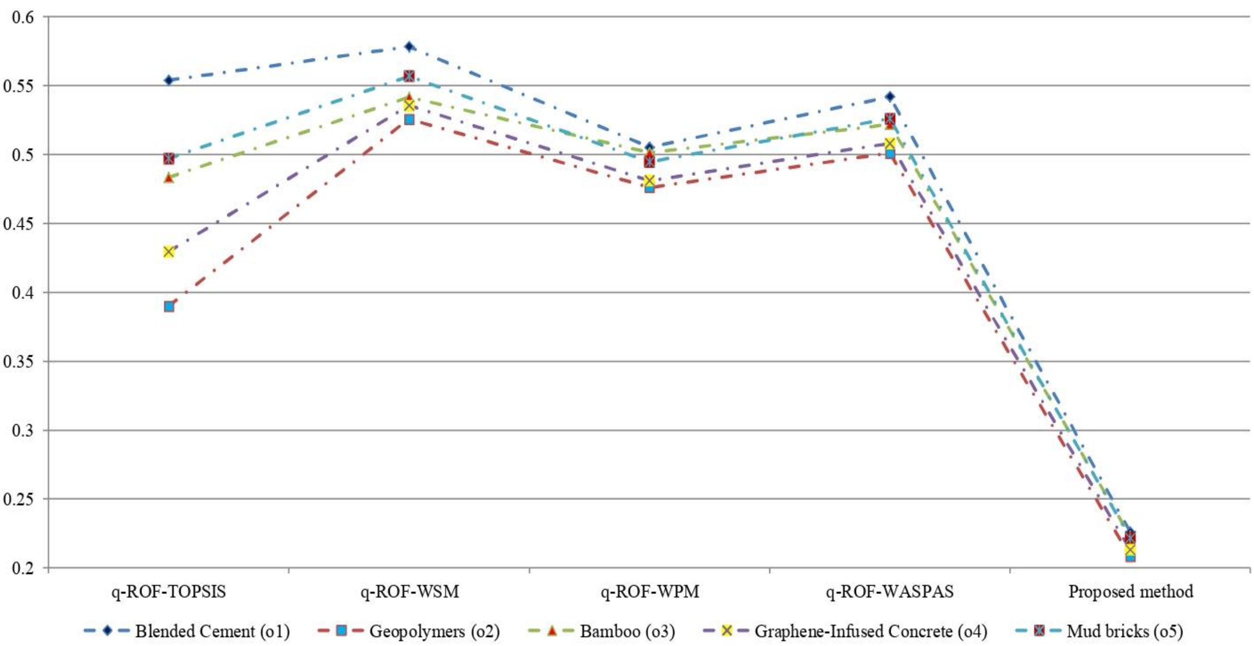

Figure 3. Comparison of utility degree of each approach for zero-/low-carbon construction material.

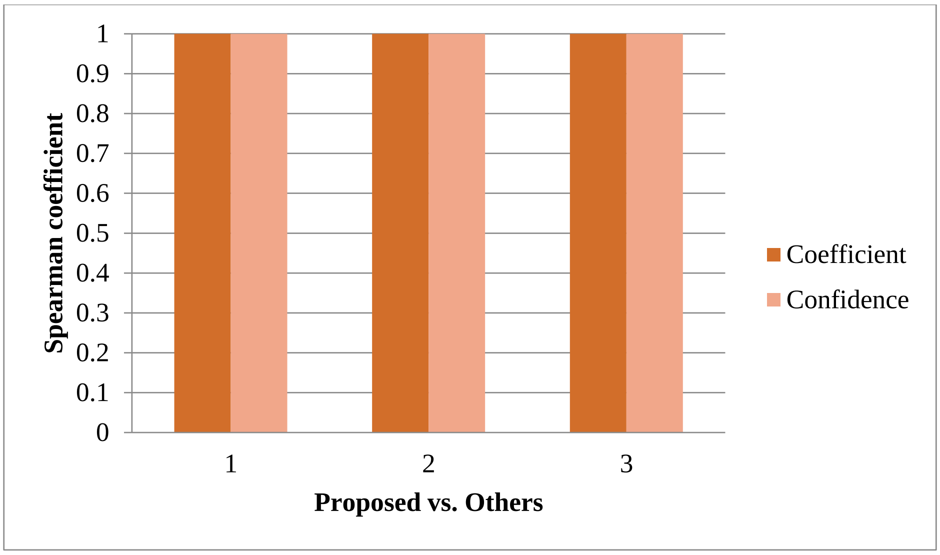

Figure 4. Variation in the utility degree of options over diverse parameters (φ) values.

4.2. Sensitivity Investigation

In this section, we present the sensitivity of the method base to diverse parameter (φ) values. In this respect, the diverse values of $\varphi \in [0,1]$ were considered for analysis, with the variation of φ aiding us in considering the sensitivity of the COPRAS tool. The prioritization of the options over the diverse parameter values are referenced in Table 9 and Figure 5. We observe that in Figure 3, the option, O_1, has the maximum rating when $\varphi = 0.0$ to 0.5, while the option, O_3, has the maximum rating when $\varphi = 0.6$ to 1.0. Moreover, the option, O_2, has the minimum rating when $\varphi = 0.0$ to 0.6, and the option, O_4, has the minimum rating when $\varphi = 0.7$ to 1.0. Therefore, the q-ROF-CRITIC-COPRAS approach has more stability for diverse parameter φ values. Furthermore, the criteria objective weights obtained by CRITIC were preserved to improve the sensitivity of the developed approach. In the aforesaid discussion, we observed that the utilization of different parameter (φ) values would provide more stability in the developed method.

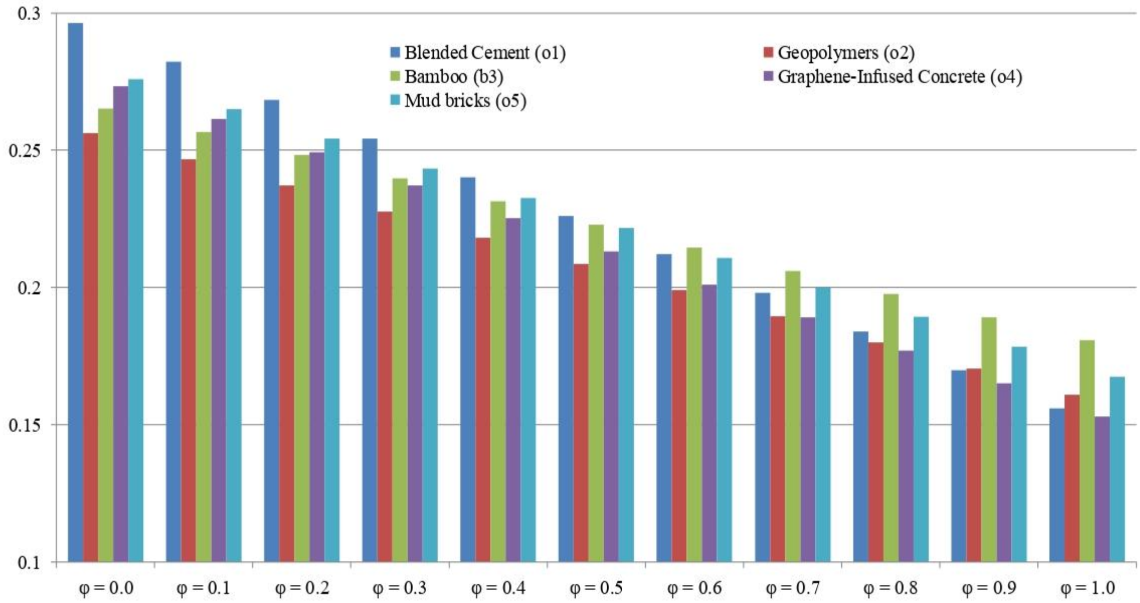

Figure 5. Variation in the UD of options over diverse parameter (φ) values.

Table 9. Utility degree of options with diverse parameter values.

φ	O_1	O_2	O_3	O_4	O_5	Ranking Order
φ = 0.0	0.2964	0.2563	0.2652	0.2733	0.2758	$O_1 \succ O_5 \succ O_4 \succ O_3 \succ O_2$
φ = 0.1	0.2823	0.2467	0.2567	0.2613	0.2650	$O_1 \succ O_5 \succ O_4 \succ O_3 \succ O_2$
φ = 0.2	0.2683	0.2372	0.2483	0.2492	0.2542	$O_1 \succ O_5 \succ O_4 \succ O_3 \succ O_2$
φ = 0.3	0.2542	0.2277	0.2398	0.2372	0.2433	$O_1 \succ O_5 \succ O_3 \succ O_4 \succ O_2$
φ = 0.4	0.2402	0.2181	0.2314	0.2252	0.2325	$O_1 \succ O_5 \succ O_3 \succ O_4 \succ O_2$
φ = 0.5	0.2261	0.2086	0.2229	0.2131	0.2217	$O_1 \succ O_3 \succ O_5 \succ O_4 \succ O_2$
φ = 0.6	0.2121	0.1991	0.2145	0.2011	0.2108	$O_3 \succ O_1 \succ O_5 \succ O_4 \succ O_2$
φ = 0.7	0.1980	0.1895	0.2060	0.1891	0.2000	$O_3 \succ O_5 \succ O_1 \succ O_2 \succ O_4$
φ = 0.8	0.1840	0.1800	0.1976	0.1770	0.1892	$O_3 \succ O_5 \succ O_1 \succ O_2 \succ O_4$
φ = 0.9	0.1699	0.1705	0.1891	0.1650	0.1783	$O_3 \succ O_5 \succ O_1 \succ O_2 \succ O_4$
φ = 1.0	0.1559	0.1609	0.1807	0.1529	0.1675	$O_3 \succ O_5 \succ O_1 \succ O_2 \succ O_4$

Table 10 provides a summarized view of different material selection decision models. It can be seen that the proposed model is unique and follows the common aspects of rational decision making. Some of the novelties of the model are listed below:

- q-ROFN was considered as the preferred style for this study It is not only flexible but also represents uncertainty from three degrees–membership, non-membership, and hesitancy. The factor, clearly controls the preference window by aiding experts in sharing their opinions flexibly.
- The criteria weights were methodically determined to properly model the competition and conflicts among the criteria. Unlike in the extant models, the interrelationships that the criteria implicitly incur were well captured by the proposed work.
- Furthermore, the hesitation of the experts during preference articulation was captured via the variability in the preference distribution. Specifically, if all experts provide the same preference for a criterion, the variability is zero, indicating that the experts have no considerable difference of opinion towards that particular criterion. A higher variability signifies a high dispersion of preferences, indicating some sense of hesitation towards a particular criterion.
- During the rank estimation, the type of criteria is actively considered, which plays a crucial role in the decision process. Unlike the extant models, the proposed work followed utility measures and ranked the alternatives from the benefit- and cost-type criteria separately. It can be seen that the proposed rank scheme is simple and elegant, with the ability to determine ranks from different angles, based on the complex proportions. Cumulatively, based on the strategy values, the rank of the alternatives is determined using the different weights for the benefit criteria and the cost criteria.

Table 10. Comparison of features of different material selection models.

Factors	Proposed	[86]	[88]	[89]
Data	q-ROFN	Fuzzy	Fuzzy	Interval-valued intuitionistic fuzzy
Criteria weights	Calculated	Directly assigned	Calculated	Calculated
Apriori information	Not needed	Not needed	Not needed	Needed
Flexible preference window	Provided	Not provided	Not provided	Not provided
Criteria interrelationship	Captured	Not captured	Not captured	Not captured
Criteria type	Considered	Considered	Considered	Considered
Total preorder	Yes	Yes	Yes	Yes
Solution measure	Utility-driven	Compromise-driven	Compromise-driven	Compromise-driven

4.3. Results and Discussion

The proposed qROF-CRITIC-COPRAS framework is the first of its kind for zero- and low-carbon material selection in a construction project at an academic institution. The integrated approaches that form the framework primarily focus on reducing human intervention so that subjectivity and biases are mitigated. By utilizing the qROF setting, the subjective randomness was resolved, and flexibility improved, thereby, supporting the experts during the preference articulation process. Moreover, the weights of the experts were determined methodically by using the Boran principle; the criteria weights were determined by adopting the CRITIC method, which effectively captures the interactions among the criteria; and, finally, the COPRAS approach was used for ranking the zero- and low-carbon materials for construction by effectively considering the nature of each criterion.

Based on the case example considered in this article, it can be observed that the design cost and the socio-economic risk contributed to approximately 20% of the significance, which implies that these two criteria played a crucial role in determining the ordering of materials for the construction project. Both these criteria belong to the cost-type criteria and have a potential role in rank determination. Following this, criteria such as safety and water pollution contributed to approximately 17% of the significance. In this, safety is of the benefit-type criteria and pollution is of the cost-type criteria. Apart from these, the other criteria were also ranked based on their significance. It can also be noted that blended cement was the highly preferred material for construction, as per the preference data in the case example discussed in this paper. This preference was followed by bamboo, mud bricks, grapheme-induced concrete, and geopolymers. This was the ordering of the materials for promoting low-carbon construction.

Some implications from the construction managers are listed below:

1. The framework is a supportive tool that considers qualitative rating information and aids in the selection of a rational material for a construction project, which is of zero- or low-carbon content. The concept of sustainable construction is fundamentally supported by the proposed framework.
2. The framework can be used by a customer who is planning a construction activity, the contractor who helps the customer in the construction project, and the material designer who manufactures such low-carbon materials for sustainable construction. Each of these entities can use the model for validating their pros and cons and can effectively refine their strategies to compete with the global market.
3. The framework can be used as a ready-made tool to assess the performance of zero- and low-carbon materials and it can be seen that the framework can be extended to different decision applications. Furthermore, the tool attempts to reduce the subjectivity and human intervention that affects the rationality of the decision process.
4. For the effective utilization of the framework in different decision problems, the stakeholders must be trained so that they gain a sense and a feel of the rationality and the mathematical support that aids their decision-making process.
5. The model primarily focuses on handling uncertainty effectively by adopting three grades–namely membership, hesitancy, and non-membership–that could effectively model uncertainty, with a flexible window for adjusting the preference zone.

5. Conclusions

The model presented in this paper is a valuable addition to the zero- and low-carbon material selection problem, which mainly concentrates on sustainable construction to promote eco-friendliness and green practices. A framework with a qROF setting was developed that not only manages subjective randomness, but also reduces human intervention, via the methodical estimation of entities. Interactions among the criteria were captured effectively and the nature of each criterion was considered during the rank determination. Specifically, the importance of experts, the weights of each criterion, and the ranking of the zero- and low-carbon materials for construction were performed stepwise, to reduce human subjectivity and the biases that would eventually arise through direct assignment.

From the comparison and sensitivity analysis, it can be observed that the proposed model is highly consistent with extant methods. Furthermore, the reliability of the method is also realized from the adequate changes to the criteria weights. Apart from these statistical benefits, the method is also theoretically attractive as it handles uncertainty effectively by reducing human intervention, capturing the interactions among the criteria, and ranking the options by properly considering the nature of the criteria. This study contributes to the promotion of zero- and low-carbon material selection, which mainly concentrates on sustainable construction in promoting eco-friendliness and green practices. The proposed model was used to evaluate five different low-carbon materials. It was distinguished that geopolymers (O_2), with an overall utility degree of 0.2261; blended cement (O_1), with an overall utility degree of 0.2229; and bamboo (O_3), with an overall utility degree of 0.2217, achieved a higher overall performance, compared to the other low-carbon materials. Some limitations of the proposed work are as follows: the data are assumed to be complete so if there is non-availability then the present system cannot handle the situation; though experts' weights are methodically determined, their interdependency is not captured effectively; and the conversion of qualitative data to qROF numbers uses predetermined values that might restrict experts in using different grades flexibly.

In the future, the authors plan to tackle the limitations mentioned above. Furthermore, different integrated approaches with diverse fuzzy settings may be used in solving the zero- and low-carbon material selection problem. Furthermore, the proposed model can also be used for other civil applications, such as the contractor-selection problem, the supplier-selection problem, the site- or location-selection problem, and may also be applied to other domains, such as business, health, and engineering. Finally, plans have been made to combine the recommendation paradigms with the decision models to solve large-scale decision problems, using reviews from web sources.

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