Green Supplier Selection using integrated novel distance measure and MARICA method under q-Rung orthopair fuzzy environment: A Case Study on Indian Railways Electrification

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Abstract

Sustainable and green practices remain highly effective for organizations in today's market characterized by intense competition, risks, and challenges. Long-term success depends not only on business revenue or performance but also on selecting the right green supplier who meets environmental, economic, and social standards. This study aims to establish a systematic, sustainability-focused methodology for identifying the optimal green supplier , in accordance with the Government of India's environmental and energy efficiency objectives. To achieve this, we introduced a novel generalized distance measure for q-Rung Orthopair Fuzzy Sets (q-ROFSs), which accounts for degrees of membership, non-membership, and hesitancy, regulated by the norm parameter α. We established that this measure fulfills essential properties. We extended the MAIRCA technique within the q-ROFS framework by integrating the proposed distance measure, which concurrently considers membership, non-membership, and hesitancy. The improved method systematically incorporates key features, such as comparing alternatives against ideal and anti-ideal solutions. A case study is assessed for ranking of green suppliers for the electrification projects of Indian Railways the proposed q-ROFS-based MAIRCA technique has been utilised. Basis on the criteria used in the strategy, it precisely identified the best suitable supplier by implementing various sustainability and performance criteria.

Keywords:q-ROFS, Green Supplier selection, Multi-criteria decision-making, MARICA, sustainability.

1 Introduction

The Viksit Bharat Vision 2047 emphasizes the significance of implementing innovative concepts in sectors such as Indian Railways. The q-rung orthopair fuzzy (q-ROF) framework represents one of these methodologies. It assists individuals in making improved decisions by managing ambiguity and complex information. New distance metrics, including those utilizing Jensen-Shannon divergence, have been developed to evaluate alternative possibilities more precisely. These are advantages for decision- making using many criteria (MCDM), such as selecting optimal rail routes or utilizing resources efficiently. The MAIRCA technique, particularly the variant utilizing Lance distance, facilitates decision-making in scenarios when the significance of each factor is uncertain. It has performed effectively in trials and may prove beneficial in actual train operations. Implementing these concepts may prove challenging due to their requirement for substantial computational resources and precise data. Fuzzy set theory Zadeh [1] has proven to be one of the most successful approaches for understanding and managing uncertainty in knowledge. Building on this foundation, researchers have progressively extended the concept to more advanced frameworks to better handle the increasing complexity and uncertainty associated with real-world problems. These extensions include intuitionistic fuzzy sets (IFS) by Atanassov [2], interval-valued intuitionistic fuzzy sets (IVIFS) by Atanassov and Gargov [3], and Pythagorean fuzzy sets (PFS)by Yager [4]. Each of these models was developed to address the challenges posed by the intricate and imprecise nature of various physical phenomena, offering more flexibility and accuracy in decision-making under uncertainty.These traditional decision-making procedures frequently fall short of addressing the inherent fuzziness and ambiguity seen in such complicated choice contexts. Gong [5] uses methods based on entropy to measure how uncertain

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linguistic fuzzy data like "high" or "low" is. They show how these methods can help make decisions when the weights are not known, using examples.Wang et al. [6] suggest suggest distance measures for q-ROFS based on the Jensen-Shannon divergence, which work better for finding patterns and making decisions when using multiple criteria.Hussain et al. [7] create belief-based OBPIs in q-ROFSs to improve the measurement of uncertainty and show that they work through instances.Dutta et al. [8] create a better method to calculate distance for q-ROFS that fixes problems with previous models. They apply this method to solve fuzzy transportation problems.Hussain et al. [9] use Hausdorff distance in q-ROFS to find similarities that can help people make decisions in real life.Rahim et al. [10] develop cosine-based similarity metrics for QOFs that improve the accuracy of investment decisions. Rani and Kumar [11] suggest a Hausdorff-based similarity measure for q-ROFSs and create a fuzzy TODIM method that has been tested in real-world situations.Khan et al. [12] talk about IVq-ROFGs that combine fuzzy sets and graph theory to explain uncertainty. They use these to model an air conditioning system.Ying et al. [13] create Cq-ROHFS to show hesitant information, which helps doctors diagnose depression using a similar score that can be adjusted. Liu and Liu [14] suggest a GDM method based on q-ROFS that keeps all the information and balances expert opinions without needing known weights.Du [15] proposes new Minkowski-style distance measures that combine different sorts of fuzzy sets for making decisions with more than one criterion.Liu and Liu [16] use q-ROHFS-based measures to improve TOPSIS for more accurate and fair decision-making, showing this through an evaluation of an energy project. Wang and Mendel [17] introduce 10 cosine and cotangent-based similarity measures for q-ROFS, which were tested in decision-making examples.Zhao et al. [18] show how p,q-QOFLSs can help manage linguistic ambiguity better by testing them in multi-criteria decision tasks. Zheng et al. [19] create a CoCoSo approach for group decisions based on IVq-ROFS and test it on a case of diagnosing sepsis. Alnefaie et al. [20] come up with q-ROFSF, which extends Pythagorean fuzzy fields to handle algebraic uncertainty. Wang et al. [21] show that q-ROSS can be used with VIKOR for qualitative decision-making, and they give real-world examples to support this. Seikh and Dey [22] use q-ROFS with VIKOR and a new TDDM metric to choose health insurance, and their method works better than older ones.Ganie [23] talks about an image fuzzy set-based distance measure that can handle responses like "abstain" or "refuse." This measure can be used for diagnosis and classification.Mateen et al. [24] use q-ROFS and VIKOR to select software reliability models, which makes decisions more accurate.Pınar et al. [25] use q-ROF TOPSIS to improve the selection of green suppliers by considering environmental issues in supply chain decisions.Dhankhar et al. [26] suggest the PDM approach for better comparison of fuzzy data using q-ROFS, which makes ranking more accurate. Kumar and Chen [27] created q-ROFWA to combine fuzzy data into GDM, which improves accuracy in unclear situations. Ahemad et al. [28] improve COPRAS by using IVq-ROFNs to assess how Indian cities handle trash. They add new ways to weight and compare data.

Cheng et al. [29] propose a decision-making model using R-numbers to handle uncertainty in multi-expert, multi-criteria situations. Experts are grouped using k-means clustering, with group importance determined by size and variety of opinions. LOPCOW is used for weighing, and CRADIS finds the best choice. The model is used in selecting hydrogen fuel supply routes. Öztaş and Öztaş [30] evaluate G20 innovation performance (2018Ű2022) using LOPCOW and MAIRCA methodologies. Human capital and research are important factors, with the United States showing the highest performance. The study also looks at the impact of COVID-19 and confirms the reliability of the method. Sedighi Khavidak et al. [31] use ENTROPY for attribute weighting and apply COBRA, MARCOS, and MAIRCA to assess six HDDs. The ENTROPY-COBRA combination is introduced. Western Digital - My Passport is recognized as the best HDD.Tešić et al. [32] suggest a FUCOM-FMAIRCA model to select Military Academy instructors. Criteria are prioritized by FUCOM, and candidates are evaluated with fuzzy MAIRCA. Sensitivity analysis confirms reliability.

Lu et al. [33] offer a Picture Fuzzy COPRAS method for sustainable supplier selection, overcoming expert uncertainty. CRITIC is used for weighting, and suppliers are ranked effectively. Practical use shows the model's usefulness in green supply chain decisions. Li et al. [34]use cloud manufacturing to find eco-friendly suppliers via a collaborative platform. This strategy boosts productivity and highlights the value of cloud tech in sustainable supplier selection. AmirSalami and Alaei [35] build a model combining Fuzzy DANP and TOPSIS to identify green suppliers and assign orders, balancing cost and sustainability. The model is applied to a medical supply case with good results. Khan et al. [36] provides a CPF-based solution that merges NLP and TOPSIS for green supplier selection using AI, cloud, and big data. The approach increases accuracy and was tested in a real-world scenario. Chen et al. [37] develop a fuzzy-rough model using SWARA for weights and ARAS for ranking providers. The model is applied in a furniture case study, with supplier S3 ranking highest, showing the method's reliability. Puška et al. [38] apply Z-numbers with fuzzy LMAW and a modified CRADIS to identify agricultural green suppliers. Key factors are price and quality, with A2 and A3 ranking highest. The model proves consistent. Ali et al. [39]extend the TODIM approach using advanced fuzzy logic to handle ambiguous green supply chain data. This enhanced method outperforms traditional approaches in a practical case. Zhang [40] analyze 193 papers (2009-2020) about green supplier selection, summarizing key methodologies and criteria. The study provides insights into effective techniques and trends in the field.Dinçer et al. [41] ormulates a methodology for the selection of green projects, emphasizing the reduction of emissions. It assesses projects with sophisticated methodologies and facilitates environmentally sustainable investment decisions.Tian and Zhang [42] employs a q-ROFS-based TODIM methodology and a PCEM system to identify green pork producers. The approach integrates ambiguity and decision-making styles, producing precise, pragmatic outcomes. Pınar et al. [43]present a q-Rung Orthopair Fuzzy TOPSIS methodology for the selection of green suppliers in the context of uncertainty. It surpasses previous methodologies and facilitates decision making in dynamic contexts. Riaz et al. [44]presents a q-ROFN-based methodology using novel aggregation operators for the identification of environmentally sustainable suppliers. The case study demonstrates enhanced precision and decision-making dependability. Liu and Qin [45] introduce a q-RIVOF-MULTIMOORA approach for extensive green supplier selection. It aggregates decision-makers and enhances multi-objective assessments, yielding consistent outcomes.Wang et al. [46]present fuzzy logic-based aggregation operators for group decision-making involving ambiguous data. The strategy demonstrates reliability and efficacy in the identification of green suppliers. Zulqarnain et al. [47] employ q-ROFSS and novel correlation coefficients in conjunction with TOPSIS for the identification of green suppliers.

Novelty of the Study

In this study:

1. We present an innovative distance metric for q-rung Orthopair fuzzy sets (q-ROFSs) that incorporates membership, non-membership, and hesitation degrees, regulated by the norm parameter alpha and the rung parameter q.

2. We examine many properties, including non-degeneracy, symmetry, boundedness, and the triangle inequality, that the suggested distance measure satisfies.

3. We enhance the multi-Attributive Ideal-Real Comparative Analysis (MARICA) approach within the (q-ROFS) framework by incorporating a unique metric, facilitating more accurate evaluation and prioritization of options in multi-criteria uncertain decision-making scenarios.

Structure of the Paper

The rest of this work is organized as follows:

1. In Section 2, we briefly examine fundamental concepts of IFSs, PFSs, FFSs, q-ROFSs, Green Supplier Selection, and the MARICA technique.

2. In Section 3, We established a novel distance metric with the required characteristics. An example of a new approach that is superior than an old one.

3. In Section 4, we expand the MARICA technique into the q-ROFS environment by utilizing an innovative distance measure that simultaneously accounts for membership, non-membership, and degrees of reluctance.

4. In Section 5, the efficacy of the proposed distance measure is demonstrated through a numerical example, wherein we implement the distance measure within the fuzzy MARICA technique for the Indian Railway Electrification Supplier Selection Case.

5. In Section 6, we concludes the paper.

2 Preliminaries

Definition 2.1. *Atanassov [2] In a universal set X, an IFS A is defined as*

$$A = \Big\{ \langle x, \kappa(x), \gamma(x) \rangle \mid x \in X \Big\}$$

where, $\forall\ x$, $\kappa(x), \gamma(x) \in [0,1]$, represents membership and non-membership degrees of x to A respectively, such that $0 \leq \kappa(x) + \gamma(x) \leq 1$ holds, and in turn, the hasitance of x to A is defined as $\pi_H = 1 - \kappa(x)\gamma(x)$. Usually the pair $\langle \kappa, \gamma \rangle$ is called an IFN.

Definition 2.2. *Yager [48] In universal set X, a q-rung orthopair fuzzy set (q-ROFS) A is represented by*

$$A = \Big\{ \langle x, \kappa(x), \gamma(x) \rangle \mid x \in X \Big\} \tag{1}$$

where, $\kappa(x)$ and $\gamma(x)$ represents membership and non-membership degrees of x belonging to the q-ROFS A, such that $\forall\ x$, $0 \leq \kappa(x), \gamma(x) \leq 1$, $0 \leq \kappa(x)^q + \gamma(x)^q \leq 1$ holds, and in turn, the hesitance of x to A is defined as $\pi_H = (1 - \kappa(x)^q - \gamma(x)^q)^{1/q}$ where $q \geq 1$. Usually, the pair $\langle \kappa, \gamma \rangle$ is called a q-rung orthopair fuzzy number (q-ROFN).

Definition 2.3. *Peng and Liu [49]Let $\mathcal{Q}_1$ and $\mathcal{Q}_2$ be two q-Rung Orthopair Fuzzy Sets (q-ROFSs) defined on a finite universe of discourse $X = \{x_1, x_2, \ldots, x_n\}$.*

The following distance measures $D_i(\mathcal{Q}_1, \mathcal{Q}_2)$ $(i = 1, 2, 3)$ are defined to quantify the dissimilarity between $\mathcal{Q}_1$ and $\mathcal{Q}_2$:

$$D_1(\mathcal{Q}_1, \mathcal{Q}_2) = \frac{1}{n} \sum_{j=1}^{n} \max \left\{ \left| \kappa^q_{\mathcal{Q}_1}(x_j) - \kappa^q_{\mathcal{Q}_2}(x_j) \right|, \left| \gamma^q_{\mathcal{Q}_1}(x_j) - \gamma^q_{\mathcal{Q}_2}(x_j) \right| \right\} \tag{2}$$

$$D_2(\mathcal{Q}_1, \mathcal{Q}_2) = \frac{2}{n} \sum_{j=1}^{n} \frac{\max \left\{ \left| \kappa^q_{\mathcal{Q}_1}(x_j) - \kappa^q_{\mathcal{Q}_2}(x_j) \right|, \left| \gamma^q_{\mathcal{Q}_1}(x_j) - \gamma^q_{\mathcal{Q}_2}(x_j) \right| \right\}}{1 + \max \left\{ \left| \kappa^q_{\mathcal{Q}_1}(x_j) - \kappa^q_{\mathcal{Q}_2}(x_j) \right|, \left| \gamma^q_{\mathcal{Q}_1}(x_j) - \gamma^q_{\mathcal{Q}_2}(x_j) \right| \right\}} \tag{3}$$

$$D_3(\mathcal{Q}_1, \mathcal{Q}_2) = \frac{2 \sum_{j=1}^{n} \max \left\{ \left| \kappa^q_{\mathcal{Q}_1}(x_j) - \kappa^q_{\mathcal{Q}_2}(x_j) \right|, \left| \gamma^q_{\mathcal{Q}_1}(x_j) - \gamma^q_{\mathcal{Q}_2}(x_j) \right| \right\}}{\sum_{j=1}^{n} \left[1 + \max \left\{ \left| \kappa^q_{\mathcal{Q}_1}(x_j) - \kappa^q_{\mathcal{Q}_2}(x_j) \right|, \left| \gamma^q_{\mathcal{Q}_1}(x_j) - \gamma^q_{\mathcal{Q}_2}(x_j) \right| \right\} \right]} \tag{4}$$

Example 2.1. *Let $\mathcal{Q}_1 = \langle 0.2, 0.4 \rangle$ and $\mathcal{Q}_2 = \langle 0.5, 0.2 \rangle$ be two q-ROFNs. By using the distance measure given in Eq. (2), it gets $D_1 = 0.0609$. And if we take $\mathcal{Q}_1 = \langle 0.2, 0.4 \rangle$ and $\mathcal{Q}_2 = \langle 0.5, 0.4 \rangle$ be two q-ROFNs. By using the distance measure given in Eq. (2), we still gets same distance $D_1 = 0.0609$.Which is not satisfactory.*

Example 2.2. *Let $\mathcal{Q}_1 = \langle 0.2, 0.4 \rangle$ and $\mathcal{Q}_2 = \langle 0.5, 0.2 \rangle$ be two q-ROFNs. By using the distance measure given in Eq. (3) and Eq. (3), it gets $D_2 = 0.1148$ and $D_3 = 0.1148$ respectively. And if we take $\mathcal{Q}_1 = \langle 0.2, 0.4 \rangle$ and $\mathcal{Q}_2 = \langle 0.5, 0.4 \rangle$ be two q-ROFNs.it gets $D_2 = 0.1148$ and $D_3 = 0.1148$ respectively. Which is not satisfactory.*

The existing distance measures fail to distinguish between cases where the non-membership degree remains constant and where it changes, resulting in identical distance values. This insensitivity to variations in either the membership or non-membership components limits their effectiveness in precise discrimination between q-ROFNs.

3 Proposed Distance Measure for q-Rung Orthopair Fuzzy Sets

Definition 3.1. *Let $\mathcal{Q}_1 = \{(\kappa_{1j}, \gamma_{1j})\}_{j=1}^n$ and $\mathcal{Q}_2 = \{(\kappa_{2j}, \gamma_{2j})\}_{j=1}^n$ be two q-Rung Orthopair Fuzzy Sets (q-ROFSs), where κ_{ij} and γ_{ij} are the membership and non-membership degrees respectively, and $\kappa^q_{ij} + \gamma^q_{ij} \leq 1$ for $i = 1, 2$ and $j = 1, 2, \ldots, n$. Define the hesitancy degree as:*

$$\pi_{ij} = \left(1 - \kappa^q_{ij} - \gamma^q_{ij}\right)^{1/q}$$

We propose the following generalized distance measure between $\mathcal{Q}_1$ and $\mathcal{Q}_2$:

$$D_{new}(\mathcal{Q}_1, \mathcal{Q}_2) = \frac{1}{n} \sum_{j=1}^{n} \left(\frac{|\kappa^q_{1j} - \kappa^q_{2j}|^\alpha + |\gamma^q_{1j} - \nu^q_{2j}|^\alpha + |\pi_{1j} - \pi_{2j}|^\alpha}{3} \right)^{1/\alpha} \tag{5}$$

where $q \geq 1$, $\alpha \geq 1$ is a norm parameter, and n is the number of elements.

Theorem 3.1 (Non-negativity)**.** *For any two q-ROFSs $\mathcal{Q}_1$ and $\mathcal{Q}_2$, the proposed distance satisfies:*

$$D_{new}(\mathcal{Q}_1, \mathcal{Q}_2) \geq 0$$

Proof. The expression under the summation in Equation (5) is a convex combination of absolute values raised to a power $\alpha \geq 1$. Since absolute values and powers of non-negative numbers are non-negative, and the root of a non-negative number is also non-negative, the overall expression is non-negative. □

Theorem 3.2 (Symmetry)**.** *The proposed distance is symmetric:*

$$D_{new}(\mathcal{Q}_1, \mathcal{Q}_2) = D_{new}(\mathcal{Q}_1, \mathcal{Q}_2)$$

Proof. The formula is symmetric with respect to indices 1 and 2, as $|\kappa_{1j}^q - \kappa_{2j}^q| = |\kappa_{2j}^q - \kappa_{1j}^q|$, and the same holds for γ and π. □

Theorem 3.3 (Identity of Indiscernibles)**.**

$$D_{new}(\mathcal{Q}_1, \mathcal{Q}_2) = 0 \iff \mathcal{Q}_1 = \mathcal{Q}_2$$

Proof. If $\mathcal{Q}_1 = \mathcal{Q}_2$, then
$kappa_{1j} = \kappa_{2j}$ and $\gamma_{1j} = \gamma_{2j}$ for all j, so all terms under the summation become zero and thus $D_{\text{new}} = 0$.

Conversely, if $D_{\text{new}} = 0$, then each term inside the summation must be zero. This implies $|\kappa_{1j}^q - \kappa_{2j}^q| = 0$, $|\gamma_{1j}^q - \gamma_{2j}^q| = 0$, and $|\pi_{1j} - \pi_{2j}| = 0$ for all j, which leads to $\_\kappa_{1j} = \kappa_{2j}$ and $\gamma_{1j} = \gamma_{2j}$ (assuming $q \geq 1$ and uniqueness of qth roots), hence $\mathcal{Q}_1 = \mathcal{Q}_2$. □

Theorem 3.4 (Boundedness)**.** *The proposed distance is bounded such that:*

$$0 \leq D_{new}(\mathcal{Q}_1, \mathcal{Q}_2) \leq 1$$

Proof. Each κ_{ij}^q, γ_{ij}^q lies in $[0, 1]$, and so does π_{ij}, since they are derived from bounded q-ROFS constraints. The maximum difference between any two corresponding terms is 1, so each D_j term inside the sum is bounded above by 1, making the average also at most 1. □

This distance measure incorporates the entire uncertainty structure of q-ROFSs, including membership, non-membership, and hesitancy, and is tunable via the norm parameter α and fuzziness parameter q.

Example 3.1. *As the existing distance measures are insufficient for the preceding example, 2.1. These restrictions are addressed by the suggested distance measure.For $\mathcal{Q}_1 = \langle 0.2, 0.4 \rangle$ and $\mathcal{Q}_2 = \langle 0.5, 0.2 \rangle$ be two q-ROFNs. By using the proposed distance measure given in Eq.* (5)*, it gives $D_{new} = 0.0759$. Similarly, For $\mathcal{Q}_1 = \langle 0.2, 0.4 \rangle$ and $\mathcal{Q}_2 = \langle 0.5, 0.4 \rangle$ be two q-ROFNs. By using the proposed distance measure given in Eq.* (5)*, it gives $D_{new} =$* 0.0719.

Hence, the proposed distance measure can handle the drawbacks of existing distance measure and give a clear output.

4 Methodology: q-ROFS-Based MAIRCA Method Using the Proposed Distance Measure

This section presents the proposed extension of the Multi-Attributive Ideal-Real Comparative Analysis (MAIRCA) method under the q-Rung Orthopair Fuzzy Set (q-ROFS) environment. The methodology incorporates a novel distance measure that captures the difference between q-ROFSs, handling membership (κ), non-membership (γ), and hesitancy (π) components jointly.

Let $\mathcal{A} = \{A_1, A_2, \ldots, A_m\}$ be the set of m alternatives and $\mathcal{C} = \{C_1, C_2, \ldots, C_n\}$ be the set of n criteria.$w_t \in [0, 1]$ and $\sum\limits_{t=1}^{s} w_t = 1$.By using the q-ROFVs $\chi_{ij} = \langle \kappa_{ij}, \gamma_{ij} \rangle$, the expert evaluates the alternative O_i with respect to the attribute C_j to construct the DMx $\widetilde{D} = (\chi_{ij})_{m \times n}$, shown as follows:

Step:1 **Construct the Initial Decision Matrix:**

$$\widetilde{D} = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_m \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \cdots & C_n \end{array} \\ \begin{pmatrix} \chi_{11} & \chi_{12} & \cdots & \chi_{1n} \\ \chi_{21} & \chi_{22} & \cdots & \chi_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \chi_{m1} & \chi_{m2} & \cdots & \chi_{mn} \end{pmatrix} \end{array}.$$

where $i = 1, 2, \ldots, m$ and $j = 1, 2, \ldots, n$.

Step:2 **Determine Ideal and Anti-Ideal Solutions:** For benefit criteria:

$$\kappa_j^+ = \max_i \kappa_{ij}, \quad \gamma_j^+ = \min_i \gamma_{ij}$$

$$\kappa_j^- = \min_i \kappa_{ij}, \quad \gamma_j^- = \gamma_i \nu_{ij}$$

For cost criteria, the definitions are reversed.

Step:3 **Construct the Theoretical Assessment Matrix:** The theoretical expectation of decision-makers' assessments is defined as:

$$T_{ij} = \frac{1}{m}, \quad \forall i = 1, \ldots, m, \ j = 1, \ldots, n$$

Step:4 **Compute the Real Assessment Matrix Using the Proposed Distance Measure:** This distance is computed for each alternative A_i under criterion C_j from the ideal (Q_j^+) and/or anti-ideal (Q_j^-) points using (5).

Step:5 **Calculate the Difference Matrix:** Compute the absolute difference between theoretical and real assessments:

$$\Delta_{ij} = |T_{ij} - D_{ij}|$$

Step:6 **Aggregate the Differences Using Criteria Weights:** Using criteria weights w_j, calculate the final score:

$$S_i = \sum_{j=1}^{n} w_j \cdot \Delta_{ij}$$

Step:7 **Rank the Alternatives:** Rank the alternatives based on ascending order of S_i; the alternative with the lowest score is closest to the ideal solution.

5 Case Study: Green Supplier Selection for Indian Railways Electrification

The Government of India has significantly prioritized the electrification of railway networks as a key strategy for reducing carbon emissions and improving energy efficiency in the transport sector. Indian Railways, being one of the largest rail networks globally, has initiated large-scale electrification projects, aligning with the nation's commitment to sustainable infrastructure and energy conservation.

In this context, selecting green suppliers for the electrification projects is of paramount importance. These suppliers are responsible for providing components such as electric traction systems, transformers, control systems, and environment-friendly installation services. The aim is to ensure that not only are the components energy efficient and recyclable but that the procurement and installation processes align with sustainability goals.

In this case study, a single decision-maker from the Railway Procurement Cell is assigned the task of selecting the most suitable green supplier from a pool of shortlisted alternatives. The decision is based on a structured evaluation of each supplier against multiple sustainability and performance-based criteria.

Table 1: Criteria for Green Supplier Evaluation in Electrification Projects

Code	Criteria	Description
C1	Quality and Reliability	Consistency of performance and long-term durability of supplied products.
C2	Environmental Certification	ISO 14001 or equivalent environmental management certifications.
C3	Green Manufacturing Process	Use of non-toxic, low-emission, and recyclable materials.
C4	Cost Competitiveness	Competitive pricing while maintaining sustainable production practices.
C5	Delivery Lead Time	Timeliness in supplying electrification components.
C6	Innovation in Eco-Tech	Use of innovative technologies to minimize environmental impact.
C7	Local Sourcing Compliance	Preference for domestic procurement aligned with "Make in India" policy.
C8	Waste Management Practice	Evidence of waste reduction and eco-disposal mechanisms.

Table 2: Alternative Green Suppliers

Code	Supplier Name	Description
A1	GreenTrak Electric Pvt. Ltd.	Known for ISO-compliant products and modular electric traction systems.
A2	Bharat Rail Infra Solutions	Offers eco-friendly packaging and emphasizes local sourcing.
A3	EcoVolt Systems	Pioneer in energy-efficient control systems and rapid delivery.
A4	EnviroRail Technologies	Specializes in green manufacturing with high innovation ratings.

The dataset illustrates realistic supplier profiles in line with Indian Railway's electrification goals. The case is relevant to actual procurement decisions made under initiatives like *Mission Electrification* and the *National Electric Mobility Mission*.

Example 5.1. *To demonstrate the applicability of the proposed fuzzy MAIRCA method with a novel q-ROFS-based distance measure, a real-world example is constructed based on the Indian Railways Electrification Supplier Selection case. An expert from the Railway Procurement Cell evaluates four shortlisted suppliers (A1-A4) across eight criteria (C1-C8).Type of criteria and weightage*

Table 3: Criteria Type and Weights

Criteria	C1	C2	C3	C4	C5	C6	C7	C8
Type	Benefit	Benefit	Benefit	Cost	Benefit	Benefit	Benefit	Benefit
Weight (w_j)	0.12	0.10	0.11	0.15	0.10	0.13	0.14	0.15

The evaluations are expressed as q-Rung Orthopair Fuzzy Numbers (q-ROFNs).
we assume $q = 3$ *and* $\alpha = 2$*for this example.*

Step 1: Construct the Initial q-ROFS Decision Matrix

Table 4: q-ROFS Decision Matrix

Alt.	**C1**	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**
A1	(0.90, 0.35)	(0.70, 0.45)	(0.70, 0.25)	(0.75, 0.37)	(0.77, 0.29)	(0.80, 0.25)	(0.90, 0.35)	(0.85, 0.50)
A2	(0.70, 0.45)	(0.70, 0.25)	(0.85, 0.10)	(0.65, 0.30)	(0.80, 0.45)	(0.85, 0.23)	(0.95, 0.41)	(0.75, 0.40)
A3	(0.68, 0.45)	(0.70, 0.45)	(0.86, 0.25)	(0.75, 0.30)	(0.70, 0.40)	(0.90, 0.45)	(0.76, 0.45)	(0.80, 0.55)
A4	(0.87, 0.29)	(0.85, 0.42)	(0.79, 0.25)	(0.85, 0.20)	(0.70, 0.55)	(0.82, 0.35)	(0.85, 0.50)	(0.79, 0.49)

Step 2: All criteria are treated as benefit-type except for C4 (Cost Competitiveness), which is a cost-type criterion.The ideal values are selected by taking the maximum κ and minimum γ for benefit-type, and minimum κ and maximum γ for cost-type criteria (C4).

Table 5: Ideal and Anti-Ideal q-ROFS Matrix

Criterion	**Ideal**	**Anti-Ideal**
C1	0.9000	0.2900
C2	0.8500	0.2500
C3	0.8600	0.1000
C4	0.3700	0.6500
C5	0.8000	0.2900
C6	0.9000	0.2300
C7	0.9500	0.3500
C8	0.8500	0.4000

Step 3: The theoretical expectation of decision-maker's assessments is defined as:

$$T_{ij} = \begin{bmatrix} 0.2500 & 0.2500 & 0.2500 & 0.2500 & 0.2500 & 0.2500 & 0.2500 & 0.2500 \\ 0.2500 & 0.2500 & 0.2500 & 0.2500 & 0.2500 & 0.2500 & 0.2500 & 0.2500 \\ 0.2500 & 0.2500 & 0.2500 & 0.2500 & 0.2500 & 0.2500 & 0.2500 & 0.2500 \\ 0.2500 & 0.2500 & 0.2500 & 0.2500 & 0.2500 & 0.2500 & 0.2500 & 0.2500 \end{bmatrix}$$

Step 4: We use the newly proposed q-ROFS fuzzy distance measure to Calculate the New Fuzzy Distance:

$$D_{ij} = \begin{bmatrix} 0.0141 & 0.1743 & 0.1900 & 0.0939 & 0.0363 & 0.1496 & 0.1128 & 0.0442 \\ 0.2539 & 0.1773 & 0.0150 & 0.0149 & 0.0446 & 0.0818 & 0.0298 & 0.1296 \\ 0.2720 & 0.1743 & 0.0101 & 0.0922 & 0.1073 & 0.0620 & 0.3032 & 0.0835 \\ 0.0516 & 0.0409 & 0.0938 & 0.2167 & 0.1277 & 0.1199 & 0.1795 & 0.0807 \end{bmatrix}$$

This distance is computed between each alternative and the ideal solution.

Step 5: Compute the absolute difference between theoretical and real assessments:

$$\Delta_{ij} = \begin{bmatrix} 0.2359 & 0.0757 & 0.0600 & 0.1561 & 0.2137 & 0.1004 & 0.1372 & 0.2058 \\ 0.0039 & 0.0727 & 0.2350 & 0.2351 & 0.2054 & 0.1682 & 0.2202 & 0.1204 \\ 0.0220 & 0.0757 & 0.2399 & 0.1578 & 0.1427 & 0.1880 & 0.0532 & 0.1665 \\ 0.1984 & 0.2091 & 0.1562 & 0.0333 & 0.1223 & 0.1301 & 0.0705 & 0.1693 \end{bmatrix}$$

Step 6: Using criteria weights w_j given in Table (3), calculate the final score:

$$S_i = \begin{bmatrix} 0.1504 \\ 0.1602 \\ 0.1314 \\ 0.1313 \end{bmatrix}$$

Step 7: Rank the Alternatives

Alternatives are ranked based on increasing total deviation from the theoretical assessment. The smaller the deviation, the better the alternative matches the ideal supplier profile.

Table 6: Final Ranking of Suppliers

Alternative	**Rank**
A4	1
A3	2
A1	3
A2	4

EnviroRail Technologies (A4) is identified as the most suitable green supplier based on the proposed distance-based q-ROFS MAIRCA method, demonstrating alignment with the sustainability and performance objectives of Indian Railways.

6 Conclusion

This study presents a straightforward and intelligent method for selection of an optimal environmentally sustainable supplier for extensive projects such as railway electrification. It extends a specialized approach to manage uncertainty and selection of suppliers based upon their adherence to environmental criteria. Upon evaluation of the Indian Railway's electrification initiative, EnviroRail Technologies emerged as the only preferred option, demonstrating the efficacy of this technology in practical uses in a very fruitful manner. This methodology assists governments and various corporations in making decisions best for environment keeping a check on quality or expense, facilitating the transition to more sustainable infrastructure. Due to escalating environmental rules and intensifying competition, it is imperative to select green suppliers particularly for significant undertakings such as the construction of electric trains. This study concludes an intelligent, straightforward and simplified method for identifying the optimal green supplier. Q ROFS methodology has been employed a to address uncertainty in decision-making. It also presents a bright and better approach for evaluation of suppliers and to identify which ones are genuinely more environmentally beneficial. The method is way ahead the existing system (designated MAIRCA) and improves its accuracy. It evaluates our expectations of a supplier against their actual deliverables and ranks them according to their proximity to the ideal selection. The approach employed for India's railway electrification project identified "EnviroRail Technologies (A4)" as the optimal green supplier. This verifies that the concept is feasible and aligns with the Indian government's objectives for environmental stewardship and energy efficiency. This system can assist other organizations or governments in selecting environmentally friendly suppliers without sacrificing quality or cost. It demonstrates that intelligent, environmentally sustainable choices are feasible, even in intricate or difficult circumstances. This research facilitates improved decision-making in the development of more sustainable and dependable infrastructure systems.

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Disclosure of Interests

The authors have no competing interests to declare that are relevant to the content of this article.

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