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A Lance Distance-Based MAIRCA Method for q-Rung Orthopair Fuzzy MCDM with Completely Unknown Weight Information

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Abstract. The purpose of this manuscript is to develop a novel MAIRCA (Multi-Attribute Ideal-Real Comparative Analysis) method to solve the MCDM (Multiple Criteria Decision-Making) problems with completely unknown weights in the q-rung orthopair fuzzy (q-ROF) setting. Firstly, the new concepts of q-ROF Lance distance are defined and some related properties are discussed in this paper, from which we establish the maximizing deviation method (MDM) model for q-ROF numbers to determine the optimal criteria weight. Then, the Lance distance-based MAIRCA (MAIRCA-L) method is designed. In it, the preference, theoretical and real evaluation matrices are calculated considering the interaction relationship in q-ROF numbers, and the q-ROF Lance distance is applied to obtain the gap matrix. Finally, we manifest the effectiveness and advantage of the q-ROF MAIRCA-L method by two numerical examples.

Key words: Lance distance measure, interaction operations, q-ROF numbers, MCDM.

1. Introduction

The MCDM is a procedure of choosing the best solution from a collection of alternatives based on the multi-criteria appraisal data given by the decision-makers. As the social and economic environment becomes more and more complex, the characteristics of human cognition and thinking are the major internal causes of vague and inaccurate judgments on decision-making problems. To accurately and effectively express evaluation information is a challenging job. After the classical fuzzy set (Zadeh, 1965), its extensions have been proposed and applied successively. For instance, the ideas of intuitionistic fuzzy set (IFS) were introduced by Atanassov (1986), some notions of Pythagorean fuzzy set (PFS) were advanced by Yager (2014) and the generalized concepts of q-ROFS were extended by

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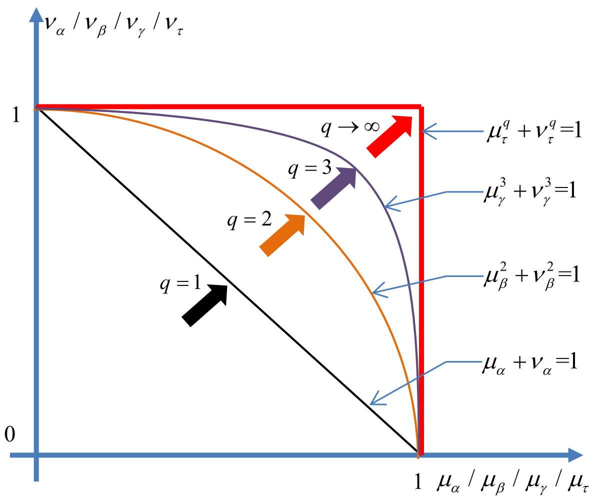

Fig. 1. The relationships of IFS, PFS and q-ROFS (Wang *et al.*, 2020a).

Yager (2017). Among these extensions, q-ROFS is considered as a viable tool which is capable of dealing with complexity, indeterminacy and ambiguity (Yager, 2017). There are membership degree (MD) ($0 \leqslant \mu \leqslant 1$) and non-membership degree (ND) ($0 \leqslant \nu \leqslant 1$) in q-ROFS, which respectively represent the degree of support and opposition of the objective belonging to this set, the MD and ND meet $\mu^q + \nu^q \leqslant 1$ (Yager, 2017). Obviously, when q values are one and two, the q-ROFS is reduced to the IFS and PFS, respectively. The relationships of IFS, PFS, and q-ROFS are revealed in Fig. 1 (Wang, *et al.*, 2020a). In addition, the parameter q value can be changed dynamically to achieve a suitable scope of information expression according to the requirements of specific decision scenarios, thus the q-ROFS can be employed to portray more uncertain and vague evaluation information.

In the q-ROF context, apart from the development of various aggregation operators (Peng and Luo, 2021; Saha *et al.*, 2022a), the alternative ranking techniques have become one of the focuses of many scholars. So far, various types of decision-making techniques have been extended and utilized in the q-ROF environment, and these methods can be classified according to their characteristics as: (1) the distance-based methods, such as TOPSIS (Dincer *et al.*, 2022; Pinar *et al.*, 2021; Ye *et al.*, 2021; Alkan and Kahraman, 2021; Pinar and Boran, 2020; Khan *et al.*, 2021b), TODIM (Krishankumar *et al.*, 2021; Chen *et al.*, 2021; Arya and Kumar, 2021; Liu *et al.*, 2021; Wang and Li, 2018), VIKOR (Khan *et al.*, 2021a; Sun *et al.*, 2021), CODAS (Deveci *et al.*, 2022a), EDAS (Darko and Liang, 2020; Liang *et al.*, 2023), and MABAC (Gong *et al.*, 2020; Wang *et al.*, 2020a); (2) the utility-based approaches, such as WASPAS (Deveci *et al.*, 2022b; Xiao *et al.*, 2022), ARAS (Mishra and Rani, 2021), COPRAS (Krishankumar *et al.*, 2019) and MARCOS (Ali, 2022); (3) the distance- and utility-based hybrid approaches, such as MULTIMOORA (Mishra *et al.*, 2022; Riaz *et al.*, 2022; Aydemir and Gunduz, 2020), PROMETHEE (Liu L. *et al.*, 2020; Akram and Shumaiza, 2021; Zhang *et al.*, 2021b), DNMA (Saha *et al.*, 2022b), CoCoSo (Deveci *et al.*, 2022c), and GLDS (Liu *et al.*, 2020; Liao *et al.*, 2020); (4) other methods, such as ORESTE (Long and Liao, 2021) and Thermodynamic (Li *et al.*, 2021; Zhang *et al.*, 2021a). These aforementioned decision-making approaches have been widely applied to handle complex decision issues in real-life, such as solid waste management (Ali, 2022; Mishra *et al.*, 2022), renewable energy management (Krishankumar *et al.*, 2019; Deveci *et al.*, 2022c), COVID-19 epidemic management (Khan *et al.*, 2021a; Alkan and Kahraman, 2021) and supply chain management (Liu *et al.*, 2020; Long and Liao, 2021; Wang and Li, 2018), etc.

In 2014, Pamucar *et al.* (2014) proposed the MAIRCA method for the first time, which has received massive attention from lots of scholars. This approach determines the best solution in view of the deviation between the defined theoretical and the real results. The merits of the MAIRCA method are described as below: (1) it can be employed to settle decision-making issues which have multitudinous criteria and alternatives; (2) it can also solve decision problems with mixed quantitative and qualitative evaluation criteria; (3) the decision process of MAIRCA is easily understood and can be flexibly applied in combination with other methods; and (4) the method has a distinctive linear normalization algorithm which can obtain highly reliable discrepancies and produce consistent results. Due to the above merits, many scholars have employed the MAIRCA to settle real-world decision issues in a great number of fields, such as flood susceptibility assessment (Hadian *et al.*, 2022), ammunition depot site selection problems (Gigovic *et al.*, 2016), biological inspiration evaluation (Zhu *et al.*, 2021), supplier performance evaluation (Chatterjee *et al.*, 2018), failure risk evaluation (Boral *et al.*, 2020), business partner selection (Trung *et al.*, 2022), and energy storage technology selection (Pamucar *et al.*, 2020). To indicate the ambiguous and indetermined evaluation information, some scholars have extended the traditional MAIRCA method by combining it into various decision environments, such as classical fuzzy sets (Gul and Ak, 2020; Boral *et al.*, 2020; Mestanza and Bakhat, 2021), fuzzy rough sets (Zhu *et al.*, 2021), spherical fuzzy sets (Trung *et al.*, 2022; Erdogan, 2022), rough sets (Chatterjee *et al.*, 2018; Pamucar *et al.*, 2017a; Bozanic *et al.*, 2020; Pamucar *et al.*, 2017b) and intuitionistic fuzzy sets (Ecer, 2022). For example, the MAIRCA method was combined with the AHP (Analytic Hierarchy Process) (Boral *et al.*, 2020; Mestanza and Bakhat, 2021) and BWM (Best-Worst Methods) (Gul and Ak, 2020) approaches for obtaining criteria weights to solve the MCDM problem in classical fuzzy sets, respectively. Pamucar *et al.* (2017a) proposed the rough BWM-MAIRCA method to deal with the wind farm site selection problems based on the geographic information system MCDM model. Similarly, in the rough set environment, Chatterjee *et al.* (2018) designed the R'DAMETEL (Rough Decision-Making Trial and Evaluation Laboratory) technique to structure the relationship between different criteria and utilized the R'ANP (Rough Analytic Network Process) method to calculate the weights; the R'MAIRCA (Rough MAIRCA) method was proposed to evaluate supplier performance; Bozanic *et al.* (2020) constructed a hybrid LBWA-IR-MAIRCA (Level Based Weight Assessment-Interval Rough-MAIRCA) MCDM model to determine the weapon structure elements in an interval-valued rough set environment. Zhu *et al.* (2021) integrated DEMATEL-MAIRCA with rough fuzzy information to evaluate biological inspiration for biologically inspired design; Ecer (2022) proposed a MAIRCA approach extended from intuitionistic fuzzy to evaluate and select COVID-19 vaccines; Trung *et al.* (2022) advanced a hybrid MCDM model integrating AHP and MAIRCA approaches in the spherical fuzzy context; Erdogan (2022) extended the SWARA (Stepwise Weight Assessment Ratio Analysis) and MAIRCA techniques under interval-valued spherical fuzzy setting. This method has been applied to various fields by many scholars (Hashemkhani Zolfani *et al.*, 2020; Ecer, 2021; Ecer *et al.*, 2022).

From the above investigation, the comments on this technique can be summarized as below:

(1) The MAIRCA technique integrated and applied with methods (e.g. AHP, ANP, DEMATEL, BWM, LBWA, and SWARA) for determining subjective criterion weights. At present, there is no integration of MAIRCA and objective criteria weighting approaches.
(2) Except for MAIRCA methods extended in rough set and interval rough set, the total gap matrix is often determined by using Euclidean distance measures (Boral *et al.*, 2020; Mestanza and Bakhat, 2021; Gul and Ak, 2020), and some scholars have also used relative closeness degree (Ecer, 2022) for defuzzification, first based on Euclidean distance, and then on traditional MAIRCA methods for alternative ranking. If we adopt the q-ROF Hamming or Euclidean distance proposed by Du (2018) (see Definition 4 below for details), the fuzzy information will be partially lost because the influence of the refusal degree in q-ROFN is neglected in these distance measures. So, we need a new distance measure to apply in MAIRCA.
(3) Some existing studies have also demonstrated that the MAIRCA method can effectively work combined with various decision environments, and it can provide a better technique to solve MCDM problems in other environments. So far this method has not been extended in q-ROFS environment. Meanwhile, it is necessary to consider the interactive operational relationship between the membership functions in q-ROFN in the MAIRCA method to avoid the counter intuitive situation.

Based on the existing researches on decision-making methods in the q-ROFS environment, we have not found that the MAIRCA approach is utilized to solve q-ROF MCDM problems. Therefore, the purpose of our article is to integrate the MAIRCA and q-ROFSs to settle the MCDM issue, this is the dominant motivation of this article. Moreover, the Hamming or Euclidean distance measures are often used in existing MAIRCA method, and some q-ROF distance measures are more sensitive to large biased data, such as Minkowski-type distance (the special cases include Euclidean, Hamming and Chebyshev), cosine distance, multi-parametric distance and projection-based distance, etc. (Peng and Luo, 2021) However, Lance distance measure can overcome this limitation and make it for biased data, and it has greater applicability. So, we will newly define Lance distance in the q-ROF environment, which is the second motivation for this paper. In addition, the some extended MAIRCA method in IFSs, spherical fuzzy sets and its extended environments did not consider the special case when the MD or ND is zero, which may have an impact on the results of alternative ranking. In order to avoid the counterintuitive phenomena during the decision process, it is necessary for us to take the interaction operations between

MD and ND of q-ROFNs into account in the extended q-ROF MAIRCA method, which is the third motivation. And some contributions of this article are presented as below:

(1) A novel Lance distance is defined by extending the Lance distance measure under the q-ROF environment;
(2) The MDM model is constructed in view of the q-ROF Lance distance to obtain the optimal objective weight vector;
(3) The new MAIRCA (MAIRCA-L) approach is advanced in q-ROF setting and improved by q-ROF Lance distance and q-ROFNs interaction operations;
(4) By numerical examples, we validate the availability and advantage of the developed methodology.

The rest of the article is arranged as below: Section 2 briefly reviews the q-ROFSs and traditional MAIRCA approach. The new q-ROF Lance distance measures are defined in Section 3. Section 4 uses the new MAIRCA-L to solve the q-ROF MCDM problems. Two numerical examples are provided to prove the validity of the developed method, and the superiorities are shown by comparative analysis and parameter analysis in Section 5. Conclusions and future plans are shown in Section 6.

2. Preliminaries

2.1. *q-Rung Orthopair Fuzzy Sets*

Definition 1 (Yager, 2017). Suppose $X = \{x_1, x_2, \dots, x_n\}$ is a finite universe. A q-ROFS Δ is defined as

$$\Delta = \left\{\left\langle x_j, \left(\mu_\Delta(x_j), \nu_\Delta(x_j)\right)\right\rangle \,\middle|\, x_j \in X\right\}, \tag{1}$$

in which $\mu_\Delta(x_j)$, $\nu_\Delta(x_j)$ are the MD and ND of element x_j belonging X to Δ, respectively. The abstention degree is $\pi_\Delta(x_j) = \sqrt[q]{1 - ((\mu_\Delta(x_j))^q + (\nu_\Delta(x_j))^q)}$. The binary (μ, ν) is named q-ROF number (q-ROFN), and for convenience, it is also simply represented as $\delta = (\mu, \nu)$, where $0 \leqslant \mu, \nu \leqslant 1$ and $\mu^q + \nu^q \leqslant 1$ $(q \geqslant 1)$.

Definition 2 (Yager, 2017). Suppose $\delta = (\mu, \nu)$ is a q-ROFN, the score and accuracy functions can be described as:

$$Sc(\delta) = \frac{1 + \mu^q - \nu^q}{2}, \quad Sc(\delta) \in [0, 1], \tag{2}$$

$$Ac(\delta) = \mu^q + \nu^q, \quad Ac(\delta) \in [0, 1]. \tag{3}$$

Definition 3. (Liu and Wang, 2018). For random two q-ROFNs, $\delta_1 = (\mu_1, \nu_1)$ and $\delta_2 = (\mu_2, \nu_2)$. Then,

(1) If $Sc(\delta_1) > Sc(\delta_2)$, then δ_1 is larger than δ_2;
(2) If $Sc(\delta_1) = Sc(\delta_2)$, then

(i) If $Ac(\delta_1) > Ac(\delta_2)$, then δ_1 is larger than δ_2;
(ii) and if $Ac(\delta_1) = Ac(\delta_2)$, then δ_1 and δ_2 are equal.

DEFINITION 4 (Du, 2018). Let $\delta_1 = (\mu_1, \nu_1)$ and $\delta_2 = (\mu_2, \nu_2)$ be arbitrary two q-ROFNs, their Minkowski distance can be described by

$$D_M(\delta_1, \delta_2) = \left(\frac{1}{2}\left(\left|\mu_1^q - \mu_2^q\right|^\gamma + \left|\nu_1^q - \nu_2^q\right|^\gamma\right)\right)^{1/\gamma}, \tag{4}$$

where, $\gamma \geqslant 1$.

(1) When $\gamma = 1$, Eq. (4) is reduced to the Hamming distance between δ_1 and δ_2, that is,

$$D_H(\delta_1, \delta_2) = \frac{1}{2}\left(\left|\mu_1^q - \mu_2^q\right| + \left|\nu_1^q - \nu_2^q\right|\right); \tag{5}$$

(2) When $\gamma = 2$, Eq. (4) is reduced to the Euclidean distance between δ_1 and δ_2, that is,

$$D_E(\delta_1, \delta_2) = \left(\frac{1}{2}\left(\left|\mu_1^q - \mu_2^q\right|^2 + \left|\nu_1^q - \nu_2^q\right|^2\right)\right)^{1/2}; \tag{6}$$

(3) When $\gamma \to \infty$, Eq. (4) is reduced to the Chebyshev distance between δ_1 and δ_2, that is,

$$D_C(\delta_1, \delta_2) = \max\left\{\left|\mu_1^q - \mu_2^q\right|, \left|\nu_1^q - \nu_2^q\right|\right\}. \tag{7}$$

DEFINITION 5. (Liu and Wang, 2018). Suppose there are two random q-ROFNs $\delta_1 = (\mu_1, \nu_1)$, $\delta_2 = (\mu_2, \nu_2)$, $\lambda > 0$. Then, their basic operations are as follows:

(1) $\delta_1 \oplus \delta_2 = \left(\sqrt[q]{1 - \prod_{i=1}^2 (1 - \mu_i^q)}, \prod_{i=1}^2 \nu_i\right)$;
(2) $\delta_1 \otimes \delta_2 = \left(\prod_{i=1}^2 \mu_i, \sqrt[q]{1 - \prod_{i=1}^2 (1 - \nu_i^q)}\right)$;
(3) $\lambda\delta_1 = \left(\sqrt[q]{1 - (1 - \mu_1^q)^\lambda}, \nu_1^\lambda\right)$;
(4) $(\delta_1)^\lambda = \left(\mu_1^\lambda, \sqrt[q]{1 - (1 - \nu_1^q)^\lambda}\right)$.

Let $\delta_1 = (0.8, 0.0)$ and $\delta_2 = (0.7, 0.4)$ be two q-ROFNs, we can obtain $\delta_1 \oplus \delta_2 = (0.904, 0.000)$ $(q = 2)$ from the above sum operation. Obviously, $\nu_2 = 0.4$ does not work at all in the operation, which is inconsistent with common sense and counter-intuitive. In order to avoid and eliminate the above scenario, Yang *et al.* (2020) proposed some interaction operation rules for q-ROFNs, $\lambda > 0$, which are described as below:

(1) $\delta_1 \oplus_I \delta_2 = \left(\sqrt[q]{1 - \prod_{i=1}^2 (1 - \mu_i^q)}, \sqrt[q]{\prod_{i=1}^2 (1 - \mu_i^q) - \prod_{i=1}^2 (1 - \mu_i^q - \nu_i^q)}\right)$;
(2) $\delta_1 \otimes_I \delta_2 = \left(\sqrt[q]{\prod_{i=1}^2 (1 - \nu_i^q) - \prod_{i=1}^2 (1 - \mu_i^q - \nu_i^q)}, \sqrt[q]{1 - \prod_{i=1}^2 (1 - \nu_i^q)}\right)$;

(3) $\lambda \cdot_I \delta_1 = \left(\sqrt[q]{1-\left(1-\mu_1^q\right)^\lambda}, \sqrt[q]{\left(1-\mu_1^q\right)^\lambda - \left(1-\mu_1^q-\nu_1^q\right)^\lambda}\right)$;

(4) $(\delta_1)^{\wedge_I \lambda} = \left(\sqrt[q]{\left(1-\nu_1^q\right)^\lambda - \left(1-\mu_1^q-\nu_1^q\right)^\lambda}, \sqrt[q]{1-\left(1-\nu_1^q\right)^\lambda}\right)$.

2.2. *Traditional MAIRCA Method* (Pamucar *et al.*, 2014)

The main idea of the traditional MAIRCA is to obtain the disparity between the ideal and actual importance degree, then synthesize the disparities under each criterion, and finally the solution with the smallest final gap distance can be considered as the optimal one. There are six steps to achieve this approach:

Step 1. The initial assessment matrix $X = [x_{ij}]_{m\times n}$ is formed on the basis of the opinions of all experts, where element x_{ij} ($i = 1, 2, \ldots, m$; $j = 1, 2, \ldots, n$) means the initial assessment value of alternative A_i under the criterion C_j.

Step 2. The preference for selecting a solution from m alternatives is calculated from the following Eq. (8), which implies that the expert is neutral in choosing an alternative, and it means that the probability of choosing an alternative is equal.

$$P_{A_i} = \frac{1}{m}; \qquad \sum_{i=1}^{m} P_{A_i} = 1. \tag{8}$$

Step 3. Calculate the theoretical evaluation matrix $T_p = [t_{pij}]_{m\times n}$. This matrix can be computed by multiplying the criteria weights and preferences of alternatives, i.e.:

$$T_p = [t_{pij}]_{n\times m} = [w_j \cdot P_{Ai}]_{n\times m}. \tag{9}$$

Step 4. Build the real evaluation matrix $T_r = [t_{rij}]_{m\times n}$. The element t_{rij} is computed by multiplying the theoretical evaluation value t_{pij} and the initial evaluation value normalized in the initial matrix, as follows in Eq. (10):

$$t_{rij} = \begin{cases} t_{pij} \cdot \left(\frac{x_{ij}-x_i^-}{x_i^+-x_i^-}\right), & \text{for } J_1, \\ t_{pij} \cdot \left(\frac{x_{ij}-x_i^+}{x_i^+-x_i^-}\right), & \text{for } J_2, \end{cases} \tag{10}$$

where x_{ij} is the element from the initial decision matrix. x_i^+ is the maximum value for any one criterion, and x_i^- is the minimum value for any one criterion. J_1 and J_2 are the benefit- and cost-type criterion, respectively.

Step 5. Determine the total gap matrix $T_g = [t_{gij}]_{m\times n}$.

$$t_{gij} = \begin{cases} 0, & \text{if } t_{pij} \leqslant t_{rij}, \\ t_{pij} - t_{rij}, & \text{if } t_{pij} > t_{rij}. \end{cases} \tag{11}$$

Step 6. Calculate the final function value Q_i ($i = 1, 2, \ldots, m$) of the criterion function for each alternatives. The alternatives are ranked, the smaller the function value, the better the solution is:

$$Q_i = \sum_{j=1}^{n} t_{gij}. \tag{12}$$

3. Lance Distance Measure for q-ROFNs

Lance and Williams (1966) proposed the Lance distance, which is less sensitive to biased data because it is independent of the units (magnitudes) of the variables and judges the distance between data in the form of a ratio, which is less affected by extravagant values. For data with large bias of criterion evaluation values, the Lance distance is better than other distances. Hence, it is a general approach for measuring distance in data analysis (Fan *et al.*, 2022).

Definition 6 (Lance and Williams, 1966). Suppose there are arbitrary two non-negative real number sets A and B, then the Lance distance between A and B is described as below:

$$D_{Lance}(A, B) = \frac{1}{n}\sum_{i=1}^{n} \frac{|u_A(y_i) - u_B(y_i)|}{u_A(y_i) + u_B(y_i)}, \tag{13}$$

where $u_A(y_i)$ and $u_B(y_i)$ are presented the elements of A and B, respectively. And the astriction is satisfied, i.e. $u_A(y_i) + u_B(y_i) \neq 0$, $y_i \in Y$, $i = 1, 2, \dots, n$.

However, we cannot directly apply Eq. (13) in the q-ROF environment, and there are two reasons: (1) The definition of Lance distance in Eq. (13) is based on real numbers, but it is not quite appropriate for q-ROFNs which consist of MD and ND. Therefore, a suitable approach is needed to achieve defining Lance distance in the q-ROF environment. (2) If different MD and ND in q-ROFNs are equal to zero at the same time, it will make the denominator in the Lance distance zero, which causes the Lance distance calculation of q-ROFNs to have no theoretical and practical meaning. Due to these reasons, we need to define a new Lance distance measure in the q-ROF context.

Definition 7. Let M and N on any set $X = \{x_1, x_2, \dots, x_n\}$ be two any q-ROFSs, where the corresponding q-ROFN is $\delta_M(x_i) = (\mu_M(x_i), \nu_M(x_i))$ and $\delta_{Ni}(x_i) = (\mu_N(x_i), \nu_N(x_i))$. Then the normalized q-ROFS Lance distance between M and N can be described as:

$$\begin{aligned} &D_{Lance}(M, N) \\ &\quad = \frac{1}{3n}\sum_{i=1}^{n}\left(\frac{|\mu_M^q(x_i) - \mu_N^q(x_i)|}{\mu_M^q(x_i) + \mu_N^q(x_i) + 1} + \frac{|\nu_M^q(x_i) - \nu_N^q(x_i)|}{\nu_M^q(x_i) + \nu_N^q(x_i) + 1} + \frac{|\pi_M^q(x_i) - \pi_N^q(x_i)|}{\pi_M^q(x_i) + \pi_N^q(x_i) + 1}\right). \end{aligned} \tag{14}$$

Theorem 1. *For any set $X = \{x_1, x_2, \dots, x_n\}$ on q-ROFS M and N, there are several properties of the Lance distance $D_{Lance}(M, N)$ between M and N as follows*:

(1) $D_{Lance}(M, N) \in [0, 1]$;
(2) $D_{Lance}(M, N) = 0$, *iff* $M = N$;
(3) $D_{Lance}(M, N) = D_{Lance}(N, M)$.

Proof. (1) $D_{Lance}(M, N) \geqslant 0$ is obvious, and it is only necessary to prove that $D_{Lance}(M, N) \leqslant 1$ is hold.

For any $i = 1, 2, \ldots, n$, there are $|\mu_M^q(x_i) - \mu_N^q(x_i)| \leqslant \mu_M^q(x_i) + \mu_N^q(x_i)$, $|\nu_M^q(x_i) - \nu_N^q(x_i)| \leqslant \nu_M^q(x_i) + \nu_N^q(x_i)$ and $|\pi_M^q(x_i) - \pi_N^q(x_i)| \leqslant \pi_M^q(x_i) + \pi_N^q(x_i)$, thus:

$$\frac{|\mu_M^q(x_i) - \mu_N^q(x_i)|}{\mu_M^q(x_i) + \mu_N^q(x_i) + 1} \leqslant 1, \qquad \frac{|\nu_M^q(x_i) - \nu_N^q(x_i)|}{\nu_M^q(x_i) + \nu_N^q(x_i) + 1} \leqslant 1,$$
$$\frac{|\pi_M^q(x_i) - \pi_N^q(x_i)|}{\pi_M^q(x_i) + \pi_N^q(x_i) + 1} \leqslant 1$$

so,

$$\frac{1}{3n}\sum_{i=1}^{n}\left(\frac{|\mu_M^q(x_i) - \mu_N^q(x_i)|}{\mu_M^q(x_i) + \mu_N^q(x_i) + 1} + \frac{|\nu_M^q(x_i) - \nu_N^q(x_i)|}{\nu_M^q(x_i) + \nu_N^q(x_i) + 1} + \frac{|\pi_M^q(x_i) - \pi_N^q(x_i)|}{\pi_M^q(x_i) + \pi_N^q(x_i) + 1}\right) \leqslant 1.$$

Therefore, $D_{Lance}(M, N) \leqslant 1$, and $0 \leqslant D_{Lance}(M, N) \leqslant 1$.

(2) If $D_{Lance}(M, N) = 0$, it is obvious that:

$$\frac{1}{3n}\sum_{i=1}^{n}\left(\frac{|\mu_M^q(x_i) - \mu_N^q(x_i)|}{\mu_M^q(x_i) + \mu_N^q(x_i) + 1} + \frac{|\nu_M^q(x_i) - \nu_N^q(x_i)|}{\nu_M^q(x_i) + \nu_N^q(x_i) + 1} + \frac{|\pi_M^q(x_i) - \pi_N^q(x_i)|}{\pi_M^q(x_i) + \pi_N^q(x_i) + 1}\right) = 0.$$

Then, $|\mu_M^q(x_i) - \mu_N^q(x_i)| = 0$, $|\nu_M^q(x_i) - \nu_N^q(x_i)| = 0$, $|\pi_M^q(x_i) - \pi_N^q(x_i)| = 0$ i.e. $\mu_M(x_i) = \mu_N(x_i)$, $\nu_M(x_i) = \nu_N(x_i)$, $\pi_M(x_i) = \pi_N(x_i)$

Obviously, $M = N$.

When $M = N$, for any $i = 1, 2, \ldots, n$, there are $|\mu_M^q(x_i) - \mu_N^q(x_i)| = 0$, $|\nu_M^q(x_i) - \nu_N^q(x_i)| = 0$, $|\pi_M^q(x_i) - \pi_N^q(x_i)| = 0$, then:

$$\frac{1}{3n}\sum_{i=1}^{n}\left(\frac{|\mu_M^q(x_i) - \mu_N^q(x_i)|}{\mu_M^q(x_i) + \mu_N^q(x_i) + 1} + \frac{|\nu_M^q(x_i) - \nu_N^q(x_i)|}{\nu_M^q(x_i) + \nu_N^q(x_i) + 1} + \frac{|\pi_M^q(x_i) - \pi_N^q(x_i)|}{\pi_M^q(x_i) + \pi_N^q(x_i) + 1}\right) = 0.$$

Then, $D_{Lance}(M, N) = 0$.

Therefore, the law (2) holds.

(3) Due to

$$\begin{aligned} &D_{Lance}(M,N)\\ &\quad=\frac{1}{3n}\sum_{i=1}^{n}\left(\frac{|\mu_M^q(x_i)-\mu_N^q(x_i)|}{\mu_M^q(x_i)+\mu_N^q(x_i)+1}+\frac{|\nu_M^q(x_i)-\nu_N^q(x_i)|}{\nu_M^q(x_i)+\nu_N^q(x_i)+1}+\frac{|\pi_M^q(x_i)-\pi_N^q(x_i)|}{\pi_M^q(x_i)+\pi_N^q(x_i)+1}\right)\\ &\quad=\frac{1}{3n}\sum_{i=1}^{n}\left(\frac{|\mu_N^q(x_i)-\mu_M^q(x_i)|}{\mu_N^q(x_i)+\mu_M^q(x_i)+1}+\frac{|\nu_N^q(x_i)-\nu_M^q(x_i)|}{\nu_N^q(x_i)+\nu_M^q(x_i)+1}+\frac{|\pi_N^q(x_i)-\pi_M^q(x_i)|}{\pi_N^q(x_i)+\pi_M^q(x_i)+1}\right)\\ &\quad=D_{Lance}(N,M). \end{aligned}$$

Therefore, $D_{Lance}(M,N)=D_{Lance}(N,M)$. □

According to Definition 7, suppose there are two arbitrary two q-ROFNs $\delta_1=(\mu_1,\nu_1)$, $\delta_2=(\mu_2,\nu_2)$. The q-ROF Lance distance measure between them is defined as

$$d_{Lance}(\delta_1,\delta_2)=\frac{1}{3}\left(\frac{|\mu_1^q-\mu_2^q|}{\mu_1^q+\mu_2^q+1}+\frac{|\nu_1^q-\nu_2^q|}{\nu_1^q+\nu_2^q+1}+\frac{|\pi_1^q-\pi_2^q|}{\pi_1^q+\pi_2^q+1}\right). \tag{15}$$

Compared with various distance measures in Definition 4, the proposed q-ROF Lance distance measure has the following two merits: (i) The MD, ND and abstention degree containing q-ROFN in Eq. (15) can more comprehensively reflect the evaluation information expressed by q-RON. (ii) In Eq. (15), the influence of biased data on the measurement result is overcome in the form of ratio, and it is more stable.

4. The MAIRCA-L Method for MCDM Problem with q-ROFNs

We design a new q-ROF MAIRCA-L-based MCDM model with completely unknown weight information in this section. The proposed q-ROF Lance distance is used to build the MDM model for identifying the weight of criterion in this method. Then, the MAIRCA method is improved by the interactive operation laws and Lance distance in q-ROFS context. Moreover, this method is integrated with the criterion weight to determine the ranking of alternatives. The flowchart of proposed methodology is shown in Fig. 2.

4.1. *Problem Statement*

The q-ROF MCDM problem is described as follows: suppose $A=\{A_1,A_2,\dots,A_m\}$ denotes a collection of alternatives, $C=\{c_1,c_2,\dots,c_n\}$ denotes a family of criteria, and the weight vector is $w=(w_1,w_2,\dots,w_n)^T$, which is meeting $0\leqslant w_j\leqslant 1$, $\sum_{j=1}^{n}w_j=1$, which is totally unknown. $\tilde{D}=[\tilde{d}_{ij}]_{m\times n}$ is denoted as the q-ROF initial evaluation matrix provided by the experts, where the element $\tilde{d}_{ij}=(\mu_{ij},\nu_{ij})$ is the experts' assessment

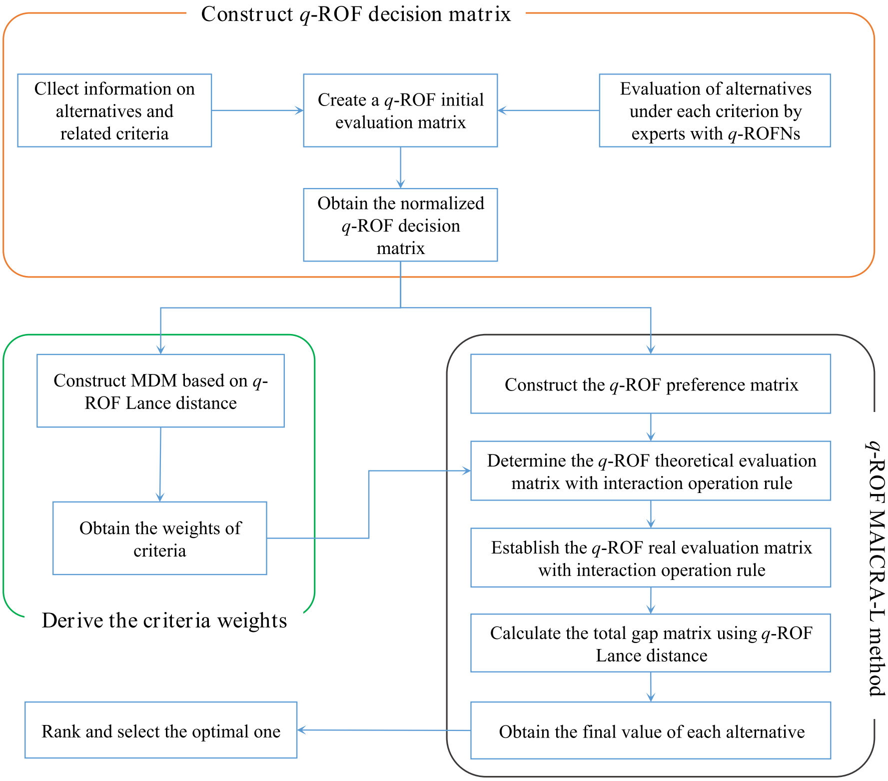

Fig. 2. Implementation flowchart of q-ROF MAIRCA-L methodology.

value of alternative h_i under criterion c_j and it is represented by q-ROFN.

$$\tilde{D} = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_m \end{array} \begin{array}{c} \begin{array}{cccc} c_1 & c_2 & \cdots & c_n \end{array} \\ \begin{bmatrix} \tilde{d}_{11} & \tilde{d}_{12} & \cdots & \tilde{d}_{1n} \\ \tilde{d}_{21} & \tilde{d}_{22} & \cdots & \tilde{d}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{d}_{m1} & \tilde{d}_{m2} & \cdots & \tilde{d}_{mn} \end{bmatrix} \end{array}.$$

As for the cost-type criterion, it needs to be normalized, which can obtained to the normalized q-ROF decision matrix $\tilde{R} = [\tilde{r}_{ij}]_{m\times n}$ $(i = 1, 2, \ldots, m;\ j = 1, 2, \ldots, n)$.

$$\tilde{r}_{ij} = \begin{cases} \tilde{d}_{ij} = (\mu_{ij}, \nu_{ij}), & c_j \in J_1, \\ (d_{ij})^c = (\nu_{ij}, \mu_{ij}), & c_j \in J_2, \end{cases} \tag{16}$$

where $(\tilde{d}_{ij})^c$ is the complement set of q-ROFN $\tilde{d}_{ij}$, J_1 and J_2 show benefit- and cost-type criteria, respectively.

4.2. *Calculate Criteria Weights Based on the MDM*

The criteria weight vector can be obtained by the MDM for the case which the criterion weight information is completely unknown. The principle of this method is that if the difference between the evaluation values of all alternatives under a criterion is small, a smaller weight value is assigned to that criterion. On the contrary, we can assign the larger weight value (Wang, 1998; Wang *et al.*, 2020b). In the q-ROF context, the proposed Lance distance measure $d_{Lance}(\tilde{r}_{ij}, \tilde{r}_{lj})$ $(i, l = 1, 2, \dots, m; i \neq l)$ is integrated into the MDM as follows:

We establish the deviation function $D_j(w)$ between all alternatives with respect to the criterion c_j, i.e.

$$D_j(w) = \sum_{i=1}^{m} D_{ij}(w) = \sum_{i=1}^{m}\sum_{l=1}^{m} d_{Lance}(\tilde{r}_{ij}, \tilde{r}_{lj}) w_j. \tag{17}$$

From this, the following mathematical model can be constructed:

$$\begin{cases} \text{Max } D(w) = \sum_{j=1}^{n}\sum_{i=1}^{m} D_{ij}(w) = \sum_{j=1}^{n}\sum_{i=1}^{m}\sum_{l=1}^{m} d_{Lance}(\tilde{r}_{ij}, \tilde{r}_{lj}) w_j, \\ \text{s.t. } \sum_{j=1}^{n} (w_j)^2 = 1, \quad 0 \leqslant w_j \leqslant 1. \end{cases} \tag{18}$$

To calculate the above model, the Lagrangian function with respect to the criteria weights and Lagrangian coefficient λ is constructed as follows:

$$L(w_j, \lambda) = \sum_{j=1}^{n}\sum_{i=1}^{m}\sum_{l=1}^{m} d_{Lance}(\tilde{r}_{ij}, \tilde{r}_{lj}) w_j + \lambda\left(\sum_{j=1}^{n} (w_j)^2 - 1\right). \tag{19}$$

$$\text{Let} \begin{cases} \dfrac{\partial L(w_j, \lambda)}{\partial w_j} = \sum_{i=1}^{m}\sum_{l=1}^{m} d_{Lance}(\tilde{r}_{ij}, \tilde{r}_{lj}) w_j + 2\lambda w_j = 0, \\ \dfrac{\partial L(w_j, \lambda)}{\partial \lambda} = \sum_{j=1}^{n} (w_j)^2 - 1 = 0. \end{cases}$$

Then, the optimal criterion weight is obtained as follows:

$$w_j^* = \frac{\sum_{i=1}^{m}\sum_{l=1}^{m} d_{Lance}(\tilde{r}_{ij}, \tilde{r}_{lj})}{\sqrt{\sum_{j=1}^{n}(\sum_{i=1}^{m}\sum_{l=1}^{m} d_{Lance}(\tilde{r}_{ij}, \tilde{r}_{lj}))^2}}. \tag{20}$$

Finally, we can normalize w_j^* to obtain the criterion weight value w_j.

$$w_j = \frac{\sum_{i=1}^{m}\sum_{l=1}^{m} d_{Lance}(\tilde{r}_{ij}, \tilde{r}_{lj})}{\sum_{j=1}^{n}\sum_{i=1}^{m}\sum_{l=1}^{m} d_{Lance}(\tilde{r}_{ij}, \tilde{r}_{lj})}. \tag{21}$$

Obviously, w_j lies in [0, 1] and $\sum_{j=1}^{n} w_j = 1$.

4.3. *The Ranking Alternatives by the q-ROF MAICRA-L Method*

Step 1. In the q-ROF environment, it is supposed that the experts are neutral for choosing options and take the same probability of selecting the alternatives into account. Then, the preference for choosing an option from the m alternatives in normalized. q-ROF decision matrix $\tilde{R} = [\tilde{r}_{ij}]_{m\times n}$ $(i = 1, 2, \dots, m;\ j = 1, 2, \dots, n)$ is computed by Eq. (22), and the q-ROF preference matrix $\tilde{P}_A = [\tilde{p}_{Aij}]_{m\times n}$ is constructed considering the interaction operation rules of q-ROFNs:

$$\begin{cases} \tilde{p}_{Aij} = \frac{1}{m} \cdot_I \big(\max_i(\mu_{ij}), \min_i(\nu_{ij})\big), \\ \quad = \left(\begin{array}{l} \sqrt[q]{1 - \big(1 - \big(\max_i(\mu_{ij})\big)^q\big)^{1/m}}, \\ \sqrt[q]{\big(1 - \big(\max_i(\mu_{ij})\big)^q\big)^{1/m} - \big(1 - \big(\max_i(\mu_{ij})\big)^q - \big(\min_i(\nu_{ij})\big)^q\big)^{1/m}} \end{array} \right) \\ \sum_{i=1}^{m} \tilde{p}_{Aij} = \big(\max_i(\mu_{ij}), \min_i(\nu_{ij})\big), \end{cases} \tag{22}$$

where $\tilde{p}_{Aij} = (\mu_{\tilde{p}ij}, \nu_{\tilde{p}ij})$.

Step 2. Determine the q-ROF theoretical evaluation matrix $\tilde{T}_p = [\tilde{t}_{pij}]_{m\times n} = [(\mu_{\tilde{t}ij}, \nu_{\tilde{t}ij})]$. We can calculate the elements $\tilde{t}_{pij}$ in the q-ROF theoretical evaluation matrix in view of the interaction operation rules of q-ROFNs defined in Definition 5.

$$\begin{cases} \tilde{T}_p = [\tilde{t}_{pij}]_{n\times m} = [w_j \cdot_I \tilde{p}_{Aij}]_{n\times m}, \\ w_j \cdot_I \tilde{p}_{Aij} = \left(\begin{array}{l} \sqrt[q]{1 - \big(1 - (\mu_{\tilde{p}ij})^q\big)^{1/w_j}}, \\ \sqrt[q]{\big(1 - (\mu_{\tilde{p}ij})^q\big)^{1/w_j} - \big(1 - (\mu_{\tilde{p}ij})^q - (\nu_{\tilde{p}ij})^q\big)^{1/w_j}} \end{array} \right), \end{cases} \tag{23}$$

where w_j is the criterion weight value which is obtained by MDM in Section 4.1.

Step 3. Establish the q-ROF real evaluation matrix $\tilde{T}_r = [\tilde{t}_{rij}]_{m\times n}$. We can also obtain the elements $\tilde{t}_{rij}$ in the q-ROF real evaluation matrix in view of the interaction operation rules of q-ROFNs.

$$\begin{aligned} \tilde{t}_{rij} &= \tilde{t}_{pij} \otimes_I \tilde{r}_{ij} \\ &= \left(\begin{array}{l} \sqrt[q]{\big(1 - \nu_{ij}^q\big)\big(1 - (\nu_{\tilde{t}ij})^q\big) - \big(1 - \mu_{ij}^q - \nu_{ij}^q\big)\big(1 - (\mu_{\tilde{t}ij})^q - (\nu_{\tilde{t}ij})^q\big)}, \\ \sqrt[q]{1 - \big(1 - \nu_{ij}^q\big)\big(1 - (\nu_{\tilde{t}ij})^q\big)} \end{array} \right). \end{aligned} \tag{24}$$

Table 1
The initial q-ROF evaluation matrix $\tilde{D}_1$ (Yang *et al.*, 2021).

	C_1	C_2	C_3	C_4
A_1	(0.64, 0.66)	(0.88, 0.42)	(0.68, 0.75)	(0.74, 0.77)
A_2	(0.57, 0.75)	(0.67, 0.44)	(0.64.0.57)	(0.54, 0.73)
A_3	(0.71, 0.63)	(0.78, 0.73)	(0.81, 0.34)	(0.63, 0.73)
A_4	(0.81, 0.50)	(0.68, 0.54)	(0.66, 0.84)	(0.76, 0.57)
A_5	(0.63, 0.62)	(0.69, 0.79)	(0.71, 0.61)	(0.80, 0.56)

Step 4. Utilize the q-ROF Lance distance (Eq. (15)) to calculate the total gap matrix $T_g = [t_{gij}]_{m\times n}$.

$$t_{gij} = \begin{cases} 0, & \text{if } sc(\tilde{t}_{pij}) \leqslant sc(\tilde{t}_{rij}), \\ d_{Lance}(\tilde{t}_{pij}, \tilde{t}_{rij}), & \text{if } sc(\tilde{t}_{pij}) > sc(\tilde{t}_{rij}). \end{cases} \tag{25}$$

Step 5. Compute the final value Q_i of the criteria function for each alternative by Eq. (12). We rank the alternatives with grade down in the light of Q_i, then the alternative is selected with the smallest value as the optimal one.

5. Numerical Examples

We verify the developed methodology in this manuscript by two numerical examples from the literature (Yang *et al.*, 2021) in this section.

EXAMPLE 1. In order to develop the business, a multinational company plans to find a local investment partner. Through initial selection, there are five candidate partners $A = \{A_1, A_2, A_3, A_4, A_5\}$ to be considered. There are four criteria $C = \{C_1, C_2, C_3, C_4\}$ to evaluate each of the five alternatives, i.e. local reputation (C_1), management level (C_2), social responsibility level (C_3) and innovation capability (C_4), with completely unknown information on the criterion weight. And the initial q-ROF evaluation matrix $\tilde{D}_1 = [\tilde{d}_{ij}]_{5\times 4}$ is constructed based on the experts' opinions, the q-ROF assessment values are presented in Table 1. It depicts the initial q-ROF evaluation matrix provided by experts, which rates alternatives over the criteria by using q-ROFNs. For example, experts rate alternative A_1 over the criterion C_1 by using q-ROFN and it is given by (0.64, 0.66), which means that the degree of membership (preference) is 0.64 and the degree of non-membership (non-preference) is 0.66.

5.1. *Decision-Making Process*

According to Section 4, the detailed decision process is given as follows:

Step 1. The criteria in this example are all benefit type and do not need to be normalized, i.e. $\tilde{D}_1 = \tilde{R}_1 = [\tilde{r}_{ij}]_{5\times 4}$. Further, the q-ROF preference matrix $\tilde{P}_A$ can be obtained by

Table 2
Gap matrix and alternatives ranking.

T_g	C_1	C_2	C_3	C_4	Q_i	Ranking
A_1	0.855	0.000	0.903	0.933	2.691	5
A_2	0.867	0.000	0.000	0.851	1.718	3
A_3	0.000	0.000	0.000	0.873	0.873	1
A_4	0.000	0.000	0.942	0.000	0.942	2
A_5	0.841	0.914	0.000	0.000	1.755	4

Eq. (22):

$$\tilde{P}_A = \begin{bmatrix} (0.52, 0.37) & (0.59, 0.34) & (0.52, 0.25) & (0.51, 0.42) \\ (0.52, 0.37) & (0.59, 0.34) & (0.52, 0.25) & (0.51, 0.42) \\ (0.52, 0.37) & (0.59, 0.34) & (0.52, 0.25) & (0.51, 0.42) \\ (0.52, 0.37) & (0.59, 0.34) & (0.52, 0.25) & (0.51, 0.42) \\ (0.52, 0.37) & (0.59, 0.34) & (0.52, 0.25) & (0.51, 0.42) \end{bmatrix}.$$

Step 2. The q-ROF MDM is implemented, and we can obtain the criterion weight vector, $w = (0.259, 0.254, 0.248, 0.239)^T$. The q-ROF theoretical evaluation matrix $\tilde{T}_p$ can be obtained by Eq. (23).

$$\tilde{T}_p = \begin{bmatrix} (0.33, 0.24) & (0.39, 0.23) & (0.34, 0.16) & (0.33, 0.28) \\ (0.33, 0.24) & (0.39, 0.23) & (0.34, 0.16) & (0.33, 0.28) \\ (0.33, 0.24) & (0.39, 0.23) & (0.34, 0.16) & (0.33, 0.28) \\ (0.33, 0.24) & (0.39, 0.23) & (0.34, 0.16) & (0.33, 0.28) \\ (0.33, 0.24) & (0.39, 0.23) & (0.34, 0.16) & (0.33, 0.28) \end{bmatrix}.$$

Step 3. A real assessment matrix $\tilde{T}_r$ with q-ROFNs is calculated by Eq. (24).

$$\tilde{T}_r = \begin{bmatrix} (0.65, 0.67) & (0.88, 0.44) & (0.69, 0.75) & (0.74, 0.78) \\ (0.58, 0.75) & (0.69, 0.46) & (0.66, 0.57) & (0.55, 0.74) \\ (0.72, 0.64) & (0.78, 0.73) & (0.82, 0.35) & (0.64, 0.74) \\ (0.81, 0.52) & (0.70, 0.55) & (0.66, 0.84) & (0.76, 0.59) \\ (0.64, 0.63) & (0.69, 0.79) & (0.72, 0.61) & (0.80, 0.58) \end{bmatrix}.$$

Steps 4–5. A total gap matrix T_g is obtained by Eq. (25), and then the final value Q_i of the criterion function with regard to each alternative is computed by Eq. (12), the final values are listed in Table 2. Therefore, the ranking result as $A_3 > A_4 > A_2 > A_5 > A_1$, the best solution is A_3.

5.2. *Comparison with Existing Methods*

We verify the feasibility and effectiveness of the developed methodology through comparative analysis with several current methods. In q-ROF environment, there are some

Table 3
The comparison results of different methods for Example 1.

Refs.	Methods	Rankings
Liu and Wang (2018)	q-ROFWA operator	$A_3 > A_1 > A_4 > A_5 > A_2$
Liu and Wang (2018)	q-ROFWG operator	$A_3 > A_1 > A_4 > A_5 > A_2$
Wei *et al.* (2018)	q-ROFWHM operator	$A_3 > A_1 > A_4 > A_2 > A_5$
Liu and Liu (2018)	q-ROFWBM operator	$A_3 > A_1 > A_4 > A_2 > A_5$
Wei *et al.* (2019)	q-ROFWMSM operator	$A_3 > A_1 > A_5 > A_2 > A_4$
Pinar *et al.* (2021)	q-ROF TOPSIS method	$A_3 > A_1 > A_4 > A_5 > A_2$
Sun *et al.* (2021)	q-ROF VIKOR method	$A_3 > A_1 > A_4 > A_5 > A_2$
This paper	q-ROF MAIRCA-L method	$A_3 > A_4 > A_2 > A_5 > A_1$

existing methods such as aggregation operators and alternative ranking techniques, including q-ROFWA (q-ROF weighted averaging) (Liu and Wang, 2018), q-ROFWG (q-ROF weighted geometric) (Liu and Wang, 2018), q-ROFWHM (q-ROF weighted Heronian mean) (Wei *et al.*, 2018), q-ROFWBM (q-ROF weighted Bonferroni mean) (Liu and Liu, 2018), q-ROFWMSM (q-ROF weighted Maclaurin symmetric mean) (Wei *et al.*, 2019), q-ROF TOPSIS (Pinetal2021), and q-ROF VIKOR (Sun *et al.*, 2021) methods. We implement the aforementioned methods in Example 1, and the computed results are listed in Table 3.

In Table 3, the results got by the proposed method are slightly different from the existing methods, but the optimal solution is always A_3, which can portray that the developed approach is feasible and effective. However, the reason for the differences in the ranking of A_1, A_2, A_4 and A_5 is that the existing methods have their own characteristics. As for the calculation process of existing various aggregation operators, they are all based on the basic algebraic operation laws, which consider the mutual independence between the MD and ND in q-ROFNs, and there is no interaction during the operations. However, these laws are also considered by numerous scholars to be unable to avoid the emergence of counterintuitive phenomena (Wang, 2021; Xing *et al.*, 2020; Gao *et al.*, 2018; He *et al.*, 2017). Although the q-ROFWBM and q-ROFWMSM operators are capable of taking into account the interrelationships between criteria in the decision-making issues, the calculation of the q-ROFWBM and q-ROFWMSM operators become more complicated when there is a larger number of criteria. In respect of existing TOPSIS and VIKOR methods, they focus on the difference between alternatives and positive ideal solution under the q-ROF context, while ignoring the interactive relationship between MD and ND in q-ROFNs, which cause them to be unable to describe these multiple heterogeneous relationships to the best advantage and be utilized to handle certain cases. In order to show the merits of the developed method, the Example 2 is given to illustrate this point.

Example 2. Based on Example 1, we change the evaluation values of A_1 and A_2 under criterion C_1 in Table 1, i.e. we obtain the revised evaluation matrix $\tilde{R}_2$, which is shown in Table 4.

As for Example 2, we further compare the q-ROFWA, q-ROFWG, q-ROFIWMSM (q-ROF interactive weighted Maclaurin symmetric mean) (Yang *et al.*, 2021) operators,

Table 4
The evaluation matrix $\tilde{R}_2$ (Yang *et al.*, 2021).

	C_1	C_2	C_3	C_4
A_1	**(0.00,0.66)**	(0.88, 0.42)	(0.68, 0.75)	(0.74, 0.77)
A_2	**(0.57,0.00)**	(0.67, 0.44)	(0.64.0.57)	(0.54, 0.73)
A_3	(0.71, 0.63)	(0.78, 0.73)	(0.81, 0.34)	(0.63, 0.73)
A_4	(0.81, 0.50)	(0.68, 0.54)	(0.66, 0.84)	(0.76, 0.57)
A_5	(0.63, 0.62)	(0.69, 0.79)	(0.71, 0.61)	(0.80, 0.56)

Table 5
The comparison results of different methods for Example 2.

Refs.	Method	Ranking
Liu and Wang (2018)	q-ROFWA operator	$A_2 > A_3 > A_1 > A_4 > A_5$
Liu and Wang (2018)	q-ROFWG operator	$A_3 > A_2 > A_4 > A_5 > A_1$
Pinar *et al.* (2021)	q-ROF TOPSIS method	$A_2 > A_4 > A_3 > A_5 > A_1$
Sun *et al.* (2021)	q-ROF VIKOR method	$A_3 > A_5 > A_1 > A_4 > A_2$
Yang *et al.* (2021)	q-ROFIWMSM operator	$A_2 > A_3 > A_1 > A_5 > A_4$
This paper	q-ROF MAIRCA-L method	$A_2 > A_3 > A_4 > A_5 > A_1$

the q-ROF TOPSIS and VIKOR methods with the developed method. The results are listed in Table 5.

The q-ROFWA and q-ROFWG operators cannot determine consistent optimal alternatives in Table 5, because both operators are based on the basic algebraic operations laws and are susceptible to the influence of extreme data when the value of MD or ND is zero in q-ROFN. In other words, the aggregation operator that is ignoring the interaction between MD and ND can exaggerate the role of special situation, leading to results of losing the significant meaning for real life decision problems. However, the ranking of presented method is consistent with the q-ROFIWMSM operator on A_2 and A_3. Moreover, the q-ROF TOPSIS and q-ROF VIKOR methods produce dissimilar ranking results for the alternatives and inconsistent optimal alternative. Among them, the q-ROF VIKOR approach cannot truly reflect the effect of the change in values $\tilde{r}_{11}$ and $\tilde{r}_{21}$ on the ranking of solutions in the process of equilibrium between group utility and individual regret, while the q-ROF TOPSIS technique can reflect this change. Compared with these methods, the designed approach not only takes into account the interactive relationship between MD and ND in q-ROFNs, but also the q-ROF Lance distance measure can effectively distinguish the variability of q-ROFNs. Therefore, the proposed method in this manuscript has more superiorities.

5.3. *Parameter Influence Analysis*

The developed method in this article contains the parameter q, which means different expression ranges of decision information. The major objective of the sensitivity analysis is to analyse the influence of changes in parameter q on the decision-making results. Therefore, we take various values in $q \in [3, 12]$ and examine the difference in the ranking

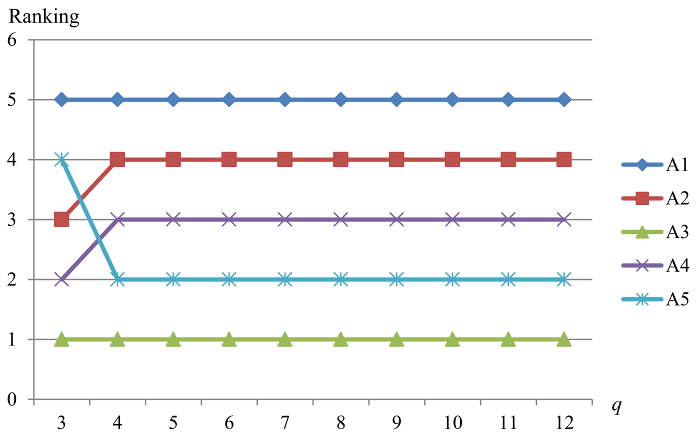

Fig. 3. The ranking results with regard to q.

results of the alternatives. The sensitivity analysis results for the parameter q appear in Fig. 3.

In Fig. 3, when the parameter $q = 3$, the ranking result is $A_3 > A_4 > A_2 > A_5 > A_1$, while when the parameter q is taken from the range of [4, 12], the ranking becomes $A_3 > A_5 > A_4 > A_2 > A_1$, in which the best solution is always A_3 and the worst is A_1. This result suggests that the influence of parameter q on the ranking of alternatives is not significant and even more stable in the method proporsed in this paper.

6. Conclusion

As for the MCDM problem with the weights completely unknown in the q-ROF environment, the MAIRCA method considering the interaction between membership functions and Lance distance measure was extended in this paper. Firstly, we briefly sorted out some relative basics; secondly, we advanced the q-ROF Lance distance measure; and then, the q-ROF MCDM model was constructed, including, using the q-ROF Lance distance measure to determine the criterion weight vector, and utilizing the extended q-ROF MAIRCA-L method for the alternative ranking. Lastly, the developed methodology was employed in two numerical examples, the effectiveness and advantage of the method were illustrated by comparing it with some existing methods.

However, there are three weaknesses in the developed methodology: (1) The proposed method is not concerned with the subjective evaluation of experts in the process of calculating the criterion weight; (2) The interrelationship between criteria cannot be captured when the MAIRCA-L method is applied to solve practical decision-making problems; (3) In determining the total gap matrix, we applied the Lance distance, which only emphasizes reducing the impact of biased data on decision results, but this is still not sufficient and comprehensive in practical decision-making problems. To remedy above shortcomings, we will explore more scientific group decision-making model considering subjective-objective combined weight information. Then, we will introduce the Bonferroni mean, Heronian mean and Hamy mean operators that can concern the interrelationship between two or multiple input arguments to integrate in MAIRCA-L method. And we will comprehensively utilize the advantages of multiple distance measures such Lance, Hamming and Euclidean in determining the total gap matrix, and the threshold parameters will be introduced to reflect decision behaviour in this process, thereby further improving the MAIRCA method.

In the future, the defined q-ROF Lance distance will be further combined with existing ranking techniques, such as MABAC (Wang *et al.*, 2020a), CODAS (Deveci *et al.*, 2022a), CoCoSo (Deveci *et al.*, 2022c) and DNMA (Saha *et al.*, 2022b), etc. And the proposed model will be extended to various decision-making environments, i.e. picture fuzzy sets (Cuong, 2014), probabilistic linguistic sets (Guo and Xu, 2016), T-spherical uncertain linguistic sets (Wang and Ullah, 2022), etc. Moreover, we will utilize the MAIRCA-L to settle practical multi-attribute group decision-making issues expressed in q-ROFNs, and we also need to use key technologies like determining the weights of experts and attributes when the information is completely unknown or partially known, and achieving group consensus to solve practical decision-making problems, such as investment decisions (Bashir *et al.*, 2021), supplier management (Liu *et al.*, 2022), technology selection (Manupati *et al.*, 2021), etc.

Conflicts of Interest

The authors declare that they have no conflicts of interest to report regarding the present study.

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