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Optimization and Distance based Parameter Reduction Under q Rung Orthopair Fuzzy Environment for Electric Vehicle Battery Design

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Abstract

Multi-criteria decision-making problems involving a large number of parameters can lead to information overload. This study proposes a novel parameter reduction framework based on q-rung orthopair fuzzy (qROF) numbers to find the same ranking of alternatives using less parameters. The proposed approach combines two complementary approaches. First, an optimization-based model is developed using score values derived from qROF membership and non-membership degrees to identify the parameters considered without changing the alternative ranking. Second, a qROF-based Minkowski distance measure is introduced to detect redundant parameters based on a predefined threshold value. In current studies, the ranking of alternatives can be partially preserved or parameter reduction can be performed randomly. The proposed approach offers a systematic approach for parameter reduction presenting the same alternative ranking. The applicability of the model is demonstrated through an electric vehicle battery design problem involving multiple criteria and alternatives. The results highlight the effectiveness and robustness of the proposed integrated approach for complex decision-making environments. It successfully reduces the number of parameter while preserving the original ranking of alternatives. The integration of optimization-based and distance-based methods ensures a more clear and interpretable parameter reduction process. The proposed methodology can also be adapted to other multi-criteria decision-making problems involving uncertainty and a large number of criteria.

Keywords: Electric vehicle battery design; Minkowski distance; Multi criteria decision making; Optimization model; Parameter reduction; qROF

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1. Introduction

In order to complete the new product development (NPD) process, a well-defined new product must be successfully introduced to the market. NPD, which begins with the planning process, continues with the output from one process becoming the input to the next process. In other words, the outputs of the planning process form the beginning of the concept development process. The final process of NPD is to make the product ready for purchase in the market [1].

Due to rapidly changing customer demands, companies must ensure timely and accurate replies to customer needs in order to gain market share. Product features are revealed in the first stage of design by considering customer needs. The establishment of subsystems is carried out during the design process. In concept selection, the best combination is selected among minimum cost and maximum performance concepts. The most important stage of NPD, concept selection, is made in the most appropriate way and the right decision is made at the beginning of the design process. Because changes that can be made in the later stages of the process are quite difficult and costly [2].

Mallahi et al. highlighted the importance of positioning in light of the increasing demand for battery charging stations for electric vehicles. It examines criterion interactions, ranking stability, and energy consumption estimation together for accurate positioning. It proposes a hybrid decision-making framework integrating the Analytic Hierarchy Process (AHP), Fuzzy Decision-Making Trial and Evaluation Laboratory (DEMATEL), and VlseKriterijumska Optimizacija I Kompromisno Resenje

(VIKOR) and Support Vector Machine. The effectiveness of the model is investigated using the Beijing example [3].

Aishwarya et al. used an approach integrating fuzzy AHP and fuzzy the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) methods to prioritize challenges and solutions in sustainable electric vehicle battery supply chains. The effectiveness of the proposed model in terms of circular economy planning was validated using sensitivity analysis [4].

Sutikno et al. examined electric vehicle battery development using seven parameters. It also explores a TOPSIS-based selection framework as a decision-making approach [5].

Kumar and Nilanjan used fuzzy AHP and fuzzy TOPSIS approaches to prioritize battery-powered, hybrid, and plug-in hybrid alternatives for electric vehicles [6].

Feng et al. proposed an integrated best worst method (BWM) and cumulative prospect theory (CPT) decision framework for selecting locations for electric vehicle battery recycling stations [7].

Recent studies have also focused on the development of advanced decision-making mechanisms under different fuzzy environments such as picture fuzzy sets [8], Pythagorean fuzzy sets [9, 10], q-rung orthopair fuzzy sets [11].

The large number of parameters in multi criteria decision making causes quite time-consuming while collecting expert opinions. The possibility of information loss increases when experts express their opinions. To simplify the complexity of such processes, various parameter reduction techniques have been introduced in the existing papers. Among these are approaches based on interval valued intuitionistic fuzzy soft set (FSS) [12], interval-valued FSS [13,14], intuitionistic FSS [15], Pythagorean FSS [16], interval-valued Neutrosophic soft set [17], bipolar hypersoft set [18].

This study handles q-rung orthopair fuzzy (qROF) number for parameter reduction. There is no study about using qROF number for parameter reduction in decision making. This paper focuses on nonchanging the ranking of all alternative. If only score value and some rankings are examined, the result can cause failure. Qin et al. used Euclidean distance to determine the unnecessary parameters. Similar parameters are sorted. They compare two parameters and randomly select one of them [14]. This random selection can cause a loss of information. This study copes with these issues.

Traditional internal combustion engine vehicles have shown lower energy efficiency and increased greenhouse gas emissions. Electric vehicles offer a solution to these challenges from an environmental and economic perspective. Batteries store energy in chemical form and power the vehicle in electrical form [19]. Electric vehicles have been increasing their market share in recent years due to the many advantages they offer. These vehicles provide significant benefits such as reduced fuel (power) consumption, lower carbon emissions, and increased overall efficiency. Powering these vehicles with sustainable energy sources significantly reduces their environmental impact. One of the most important components in powering electric vehicles is the battery. The performance, efficiency, and safety of such vehicles largely depend on the design and integrity of this battery pack [20].

This work proposes qROF number based Minkowski distance and defines parameters that can be extracted. Furthermore, it presents an optimization based approach and determines necessary parameters without changing the ranking of alternative. This paper simultaneously uses these two results and reach a decision.

Fuzzy set theory deals with uncertainty in decision-making problems. Intuitionistic fuzzy sets (IFSs) introduced by Atanassov handle membership and non-membership degrees. However, the basic logic of IFSs is the condition that the sum of membership and non-membership degrees must not exceed one. This logic can be insufficient to model more complex uncertain information [21]. To overcome this limitation, Yager proposed Pythagorean fuzzy number (PFN), which is the square total of membership degree and non-membership degree is smaller than or equivalent to 1. This extension provided greater flexibility in expressing uncertainty. However, it can be insufficient for highly complex decision-making environments [22]. Yager presented the qROF number, in which the total of the q^{th} power of membership degree and the q^{th} power of non-membership degree is smaller than or equivalent to 1 [23]. This generalization significantly enlarges the domain of permissible values and enhances the capability of modeling uncertain and imprecise information. Due to this flexibility, qROF numbers have gained increasing attention in multi-criteria decision-making problems.

Although numerous studies have focused on parameter reduction and fuzzy decision-making frameworks, several important research gaps still exist in the literature. First, existing parameter reduction approaches generally focus on classical fuzzy, intuitionistic fuzzy, or Pythagorean fuzzy environments, while studies based on qROF number remain limited. Second, many existing methods evaluate only partial ranking preservation or focus solely on identifying the best alternative after parameter reduction. However, preserving the same ranking of alternatives is critically important for reliable decision-making processes. In addition, several studies eliminate similar parameters randomly after distance or similarity analysis. This situation may lead to information loss and unstable decision results. Therefore, there is a need for a more systematic parameter reduction framework that can both preserve the ranking of alternative and reduce the parameters under uncertain decision-making environments. Motivated by these limitations, this study proposes an integrated qROF number-based parameter reduction framework. It combines the optimization-based ranking preservation and distance-based parameter reduction mechanisms for multi-criteria decision-making problems.

The contributions of the paper are presented as follows:

* A novel integrated parameter reduction framework is proposed. This combines optimization based ranking preservation and qROF number-based distance analysis in a unified structure.

* Minkowski distance based on q-ROF number is utilized to determine the distinction between two q-ROF numbers. The decision whether to reduce the criteria is made after comparing this difference with the predetermined threshold value. This presents a novel approach to the criteria reduction issue.
* The existing papers focus on criteria reduction by using the score value. These studies neglect all ranking of alternatives and only examine the top alternative or the first three alternatives. This paper handles all ranking of alternatives so that the same ranking is protected after criteria reduction. This approach is also suitable for large number of criteria and ensures fast solution. This study firstly achieves the score value of each alternative and secondly it presents an optimization approach, which cope with the abovementioned limitations.
* The proposed method is handled at electric vehicle battery design application to examine its effectiveness and working.

The remainder of this paper is organized as follows. Section 2 presents the theoretical background and the proposed qROF-based parameter reduction framework. Section 3 provides the electric vehicle battery design application and discusses the obtained results. Section 4 discusses the advantages, limitations, and implications of the proposed approach. Finally, Section 5 concludes the study and presents possible directions for future research.

2. Methodology

The primary objective of the qROF-based integrated parameter reduction framework is to reduce the number of criteria while preserving the same ranking of alternatives. The proposed framework consists of two stages. The first stage is an optimization-based model that identifies indispensable criteria by ensuring that the relative ordering of alternatives remains unchanged. The second stage is a qROF-based Minkowski distance mechanism that detects redundant criteria based on similarity analysis under a predefined threshold.

Unlike existing approaches, which often rely on partial ranking preservation or random elimination of criteria, the proposed framework integrates these two mechanisms in a systematic way. This integration eliminates the randomness in decision-making and ensures consistency, robustness, and interpretability in the parameter reduction process.

A q-ROFN $\tilde{Q}$ in a finite universe of discourse Y is indicated by $\tilde{Q}=\left\{\left(y,\mu_{\tilde{Q}}(y),v_{\tilde{Q}}(y)\right)\mid y\in Y\right\}$ where $\mu_{\tilde{Q}}:Y\to[0,1]$ $v_{\tilde{Q}}:Y\to[0,1]$, $\mu_{\tilde{Q}}(y)$ and $v_{\tilde{Q}}(y)$ represent the membership degree and non-membership degree of $y\in Y$, respectively, with the condition $0\le\mu_{\tilde{Q}}(y)^q+v_{\tilde{Q}}(y)^q\le 1, q\ge 1$. The hesitant degree of $y\in Y$, is shown as $\pi_{\tilde{Q}}(y)=\left(1-\mu_{\tilde{Q}}(y)^q-v_{\tilde{Q}}(y)^q\right)^{1/q}\ 0\le\mu_{\tilde{Q}}(y)^q+v_{\tilde{Q}}(y)^q\le 1, q\ge 1$. [23].
Let be $\tilde{Q}_1=(\mu_1,v_1)$ and $\tilde{Q}_2=(\mu_2,v_2)$ two q-ROFNs. Some operations of q-ROFNs are presented as follows [24]:

$$\tilde{Q}_1\oplus\tilde{Q}_2=\left(\left(\mu_1^q+\mu_2^q-\mu_1^q\mu_2^q\right)^{1/q},v_1v_2\right) \tag{1}$$

$$\tilde{Q}_1\otimes\tilde{Q}_2=\left(\mu_1\mu_2,\left(v_1^q+v_2^q-v_1^qv_2^q\right)^{1/q}\right) \tag{2}$$

$$\lambda\tilde{Q}_1=\left(\left(1-\left(1-\mu_1^q\right)^{\lambda}\right)^{1/q},\left(v_1\right)^{\lambda}\right),\lambda>0 \tag{3}$$

$$\tilde{Q}_1^{\lambda}=\left(\mu_1^{\lambda},\left(1-\left(1-v_1^q\right)^{\lambda}\right)^{1/q}\right),\lambda>0 \tag{4}$$

The score function $S\left(\tilde{Q}\right)$ and the accuracy function $H\left(\tilde{Q}\right)$ of the q-ROFN $\tilde{Q}$ are defined below [24]:

$$S\left(\tilde{Q}\right)=\left(1+\mu^q-v^q\right)/2, S\left(\tilde{Q}\right)\in[-1,1] \tag{5}$$

$$H\left(\tilde{Q}\right)=\mu^q+v^q, H\left(\tilde{Q}\right)\in[0,1] \tag{6}$$

Two q-ROFNs $\tilde{Q}_1=(\mu_1,v_1)$ and $\tilde{Q}_2=(\mu_2,v_2)$ are compared.
If $S\left(\tilde{Q}_1\right)>S\left(\tilde{Q}_2\right)$, then $\tilde{Q}_1>\tilde{Q}_2$;
If $H\left(\tilde{Q}_1\right)>H\left(\tilde{Q}_2\right)$, then $\tilde{Q}_1>\tilde{Q}_2$;
If $S\left(\tilde{Q}_1\right)=S\left(\tilde{Q}_2\right)$ and $H\left(\tilde{Q}_1\right)=H\left(\tilde{Q}_2\right)$, then $\tilde{Q}_1=\tilde{Q}_2$.
The q-rung orthopair fuzzy weighted averaging (q-ROFWA) operator, where $\alpha_k=\left(\mu_k(x),v_k(x)\right),(k=1,2,...,n)$ is a collection of q-ROFNs, is used [24].

$$q-ROFWA(\alpha_1,\alpha_2,...,\alpha_l)=\left(\left(1-\prod_{k=1}^{l}\left(1-\mu_k(x)^q\right)^{\lambda_k}\right)^{1/q},\prod_{k=1}^{l}v_k(x)^{\lambda_k}\right) \tag{7}$$

Let be $\tilde{Q}_i=(\mu_i,v_i)$ and $\tilde{Q}_j=(\mu_j,v_j)$ two q-ROFNs. Minkowski distance is utilized to determine the difference $\bar{d}_{ij}$ between two q-ROF numbers [25]:

$$\bar{d}_{ij}=\left(\frac{1}{2}\left|\mu_i-\mu_j\right|^q+\frac{1}{2}\left|v_i-v_j\right|^q\right)^{1/q} \tag{8}$$

Let $GLV_i=\{GLV_1,GLV_2,...,GLV_n\}$ and $CIR_j=\{CIR_1,CIR_2,...,CIR_m\}$ represent the sets of alternatives and criteria, respectively. Define $\tilde{Q}_{ij}=(\mu_{ij},v_{ij})$ as a qROFN, where each $\tilde{Q}_{ij}=(\mu_{ij},v_{ij})$ corresponds to the evaluation of the j[th] criterion for the i[th] alternative. The score value $c_i(j)$ corresponding to the membership degree of the i[th] alternative is computed using Eq. (9):

$$c_i(j)=\sum_{k=1}^{n}\left(\mu_{ij}-\mu_{kj}\right) \tag{9}$$

The score value $d_i(j)$ corresponding to the nonmembership degree of the i[th] alternative is computed using Eq. (10):

$$d_i(j)=\sum_{k=1}^{n}\left(v_{ij}-v_{kj}\right) \tag{10}$$

The overall score for GLV_i (r_i) is computed using Eq. (11):

$$r_i=\sum_{j=1}^{m}\left(c_i(j)-d_i(j)\right) \tag{11}$$

3. Electric vehicle battery design application

Evaluations were carried out by three domain experts, who rated the alternatives based on the criteria using the linguistic terms defined in Table 1.

Electric vehicle battery evaluation involves consideration of multiple criteria. In this study, eleven specific criteria, as listed

in Table 2, were taken into account, and ten electric vehicle battery alternatives were assessed. Evaluations were carried out by three domain experts, who rated the alternatives based on the criteria using the linguistic terms defined in Table 1. The aggregated expert evaluations are provided in Table 3.

Table 1. The linguistic terms

Very weak (VW)	(0.15, 0.99)
Weak (W)	(0.2, 0.85)
Moderate (M)	(0.5, 0.5)
Strong (S)	(0.85, 0.2)
Very strong (VS)	(0.99, 0.15)

Using an appropriate aggregation operator, the individual assessments provided by the three experts were consolidated to form a collective group evaluation. This study used a q value of 3 for the qROF numbers.

Based on this aggregation listed in Table 4, the score values corresponding to the membership degrees of the qROF numbers were computed and are presented in Table 5. Similarly, Table 6 displays the calculated score values associated with the non-membership degrees. Table 7 shows the overall score for each alternative.

Table 2. The handled criteria and alternatives

CIR1	Life cycle
CIR2	Nominal voltage
CIR3	Cost
CIR4	Energy density
CIR5	Power density
CIR6	Performance
CIR7	Safety
CIR8	c-rate
CIR9	Thermal stability
CIR10	Charge speed
CIR11	Weight
EVB1	Lead acid
EVB2	Advanced lead acid
EVB3	Metal foil lead acid
EVB4	Nickel iron
EVB5	Nickel zinc
EVB6	Nickel cadmium
EVB7	Nickel metal hydride
EVB8	Lithium iron
EVB9	Aluminum air
EVB10	Zinc air

The optimization model was constructed based on the overall score values obtained for each alternative. The primary objective of the model is to protect the original order of alternatives after parameter reduction. For this purpose, the score values corresponding to each criterion were incorporated into the optimization framework as coefficients. First, the total ranking scores of the alternatives were calculated using the aggregated qROF evaluations presented in Table 7. Then, pairwise ranking relationships between alternatives were established according to the original order.

The mathematical constraints given in Equations (12)–(26) were generated to ensure that the relative ranking positions of the alternatives remain unchanged during the parameter reduction process. In the optimization model, binary decision variables were assigned to each criterion.

Table 3. The opinions of the experts

		EVB1	EVB2	EVB3	EVB4	EVB5	EVB6	EVB7	EVB8	EVB9	EVB10
E1	CIR1	W	M	M	S	M	M	M	VS	W	W
	CIR2	M	M	M	W	M	M	M	S	VW	VW
	CIR3	VS	S	S	M	M	M	M	W	W	W
	CIR4	VW	W	VW	W	W	W	M	VS	S	S
	CIR5	M	M	M	W	M	M	M	S	W	W
	CIR6	W	M	M	M	M	M	M	VS	M	M
	CIR7	M	M	M	S	M	W	M	S	W	W
	CIR8	W	M	M	W	M	M	M	S	VW	VW
	CIR9	M	M	M	S	M	M	M	S	W	W
	CIR10	W	M	M	W	M	M	M	S	VW	VW
	CIR11	VW	W	W	M	M	M	S	VS	VS	S
E2	CIR1	W	W	M	W	M	W	M	S	VW	M
	CIR2	W	M	M	W	S	W	W	VS	VW	VW
	CIR3	S	S	M	VW	VW	W	W	M	M	VW
	CIR4	VW	W	W	W	VW	W	W	S	M	S
	CIR5	W	M	M	VW	W	VW	S	M	VW	W
	CIR6	W	W	W	W	M	M	S	S	S	S
	CIR7	W	W	M	VS	M	W	S	M	W	VW
	CIR8	W	W	M	M	M	W	S	VS	W	W
	CIR9	M	M	M	VS	S	VS	M	VS	VW	W
	CIR10	W	M	W	VW	VW	W	M	S	VW	VW
	CIR11	VW	M	M	W	M	M	S	VS	VS	S
E3	CIR1	M	W	M	W	W	W	S	VS	W	M
	CIR2	M	M	M	VW	M	VW	S	M	W	VW
	CIR3	VS	S	M	VW	M	W	M	VW	W	M
	CIR4	VW	M	W	W	W	W	W	S	M	S
	CIR5	W	W	W	W	W	VW	S	S	M	M
	CIR6	W	M	W	W	M	M	W	S	W	M
	CIR7	W	M	W	S	M	W	M	S	M	VW
	CIR8	M	W	W	W	M	W	W	S	VW	W
	CIR9	M	W	W	S	VS	VS	M	M	VW	M
	CIR10	M	W	W	VW	W	M	M	VS	W	VW
	CIR11	W	W	M	M	M	W	M	VS	S	VS

Table 4. The aggregated matrix

	EVB1 (μ,v)	EVB2 (μ,v)	EVB3 (μ,v)	EVB4 (μ,v)	EVB5 (μ,v)	EVB6 (μ,v)	EVB7 (μ,v)	EVB8 (μ,v)	EVB9 (μ,v)	EVB10 (μ,v)
CIR1	(0.370, 0.706)	(0.384, 0.687)	(0.500, 0.500)	(0.684, 0.477)	(0.441, 0.602)	(0.384, 0.687)	(0.700, 0.363)	(0.981, 0.161)	(0.190, 0.883)	(0.431, 0.618)
CIR2	(0.460, 0.571)	(0.500, 0.500)	(0.500, 0.500)	(0.186, 0.897)	(0.660, 0.398)	(0.380, 0.725)	(0.685, 0.414)	(0.900, 0.256)	(0.171, 0.939)	(0.150, 0.990)
CIR3	(0.981, 0.161)	(0.850, 0.200)	(0.717, 0.347)	(0.378, 0.753)	(0.458, 0.593)	(0.384, 0.687)	(0.460, 0.571)	(0.333, 0.785)	(0.338, 0.744)	(0.367, 0.733)
CIR4	(0.150, 0.990)	(0.370, 0.706)	(0.183, 0.903)	(0.200, 0.850)	(0.190, 0.883)	(0.200, 0.850)	(0.384, 0.687)	(0.952, 0.178)	(0.717, 0.347)	(0.850, 0.200)
CIR5	(0.384, 0.687)	(0.441, 0.602)	(0.441, 0.602)	(0.190, 0.883)	(0.384, 0.687)	(0.378, 0.753)	(0.775, 0.289)	(0.807, 0.251)	(0.367, 0.733)	(0.370, 0.706)
CIR6	(0.200, 0.850)	(0.460, 0.571)	(0.384, 0.687)	(0.384, 0.687)	(0.500, 0.500)	(0.500, 0.500)	(0.634, 0.479)	(0.952, 0.178)	(0.634, 0.479)	(0.660, 0.398)
CIR7	(0.384, 0.687)	(0.460, 0.571)	(0.441, 0.602)	(0.927, 0.186)	(0.500, 0.500)	(0.200, 0.850)	(0.660, 0.398)	(0.807, 0.251)	(0.370, 0.706)	(0.174, 0.931)
CIR8	(0.370, 0.706)	(0.384, 0.687)	(0.441, 0.602)	(0.338, 0.744)	(0.500, 0.500)	(0.384, 0.687)	(0.634, 0.479)	(0.927, 0.186)	(0.166, 0.953)	(0.183, 0.903)
CIR9	(0.500, 0.500)	(0.441, 0.602)	(0.441, 0.602)	(0.927, 0.186)	(0.921, 0.261)	(0.960, 0.243)	(0.500, 0.500)	(0.900, 0.256)	(0.174, 0.931)	(0.370, 0.706)
CIR10	(0.370, 0.706)	(0.441, 0.602)	(0.384, 0.687)	(0.174, 0.931)	(0.381, 0.714)	(0.460, 0.571)	(0.500, 0.500)	(0.945, 0.181)	(0.171, 0.939)	(0.150, 0.990)
CIR11	(0.171, 0.939)	(0.338, 0.744)	(0.431, 0.618)	(0.460, 0.571)	(0.500, 0.500)	(0.441, 0.602)	(0.786, 0.276)	(0.990, 0.150)	(0.975, 0.166)	(0.945, 0.181)

Table 5. The score value $c_i(j)$ for membership degree

	EVB1	EVB2	EVB3	EVB4	EVB5	EVB6	EVB7	EVB8	EVB9	EVB10
CIR1	-1.365	-1.225	-0.064	1.776	-0.655	-1.225	1.936	4.744	-3.165	-0.756
CIR2	0.005	0.408	0.408	-2.737	2.004	-0.788	2.263	4.410	-2.882	-3.092
CIR3	4.542	3.234	1.908	-1.488	-0.687	-1.428	-0.670	-1.932	-1.886	-1.594
CIR4	-2.696	-0.497	-2.364	-2.196	-2.297	-2.196	-0.357	5.320	2.979	4.304
CIR5	-0.698	-0.127	-0.127	-2.638	-0.698	-0.758	3.209	3.538	-0.864	-0.837
CIR6	-3.307	-0.710	-1.468	-1.468	-0.307	-0.307	1.034	4.209	1.034	1.289
CIR7	-1.083	-0.326	-0.513	4.349	0.078	-2.922	1.674	3.153	-1.223	-3.187
CIR8	-0.627	-0.488	0.082	-0.946	0.673	-0.488	2.014	4.944	-2.672	-2.494
CIR9	-1.134	-1.725	-1.725	3.137	3.078	3.467	-1.134	2.867	-4.398	-2.434
CIR10	-0.275	0.434	-0.136	-2.239	-0.161	0.622	1.025	5.471	-2.265	-2.475
CIR11	-4.327	-2.656	-1.728	-1.440	-1.036	-1.627	1.826	3.864	3.715	3.409

Table 6. The score value $d_i(j)$ for nonmembership degree

	EVB1	EVB2	EVB3	EVB4	EVB5	EVB6	EVB7	EVB8	EVB9	EVB10
CIR1	1.375	1.190	-0.685	-0.920	0.336	1.190	-2.056	-4.073	3.146	0.498
CIR2	-0.480	-1.190	-1.190	2.776	-2.213	1.062	-2.047	-3.625	3.196	3.710
CIR3	-3.964	-3.576	-2.110	1.958	0.356	1.299	0.134	2.277	1.868	1.758
CIR4	3.305	0.465	2.440	1.905	2.236	1.905	0.280	-4.812	-3.129	-4.595
CIR5	0.680	-0.174	-0.174	2.636	0.680	1.338	-3.309	-3.680	1.139	0.865
CIR6	3.171	0.380	1.545	1.545	-0.329	-0.329	-0.541	-3.547	-0.541	-1.353
CIR7	1.191	0.026	0.337	-3.822	-0.683	2.817	-1.707	-3.168	1.376	3.631
CIR8	0.611	0.426	-0.428	0.995	-1.449	0.426	-1.661	-4.587	3.081	2.586
CIR9	0.212	1.233	1.233	-2.927	-2.179	-2.360	0.212	-2.223	4.527	2.272
CIR10	0.238	-0.801	0.053	2.493	0.320	-1.112	-1.821	-5.013	2.564	3.079
CIR11	4.639	2.697	1.436	0.963	0.253	1.274	-1.990	-3.247	-3.088	-2.938

Table 7. The overall score r_i for GLV_i

	EVB1	EVB2	EVB3	EVB4	EVB5	EVB6	EVB7	EVB8	EVB9	EVB10
CIR1	-2.739	-2.415	0.620	2.696	-0.991	-2.415	3.992	8.817	-6.311	-1.254
CIR2	0.485	1.598	1.598	-5.513	4.217	-1.850	4.310	8.034	-6.078	-6.802
CIR3	8.506	6.809	4.018	-3.446	-1.042	-2.727	-0.804	-4.208	-3.754	-3.352
CIR4	-6.001	-0.961	-4.803	-4.101	-4.533	-4.101	-0.637	10.132	6.108	8.899
CIR5	-1.377	0.047	0.047	-5.273	-1.377	-2.097	6.518	7.218	-2.003	-1.702
CIR6	-6.477	-1.090	-3.013	-3.013	0.023	0.023	1.575	7.756	1.575	2.642
CIR7	-2.275	-0.352	-0.850	8.170	0.761	-5.739	3.380	6.321	-2.599	-6.818
CIR8	-1.238	-0.914	0.511	-1.941	2.122	-0.914	3.675	9.531	-5.753	-5.080
CIR9	-1.346	-2.957	-2.957	6.063	5.257	5.827	-1.346	5.090	-8.925	-4.706
CIR10	-0.513	1.235	-0.189	-4.732	-0.481	1.734	2.847	10.484	-4.829	-5.553
CIR11	-8.966	-5.353	-3.164	-2.403	-1.290	-2.901	3.817	7.110	6.802	6.347
Toplam	-21.943	-4.354	-8.184	-13.493	2.666	-15.160	27.327	76.285	-25.766	-17.379

This research introduces an optimization strategy, detailed as follows, calculated using Equations 12-26:

$$x_j : \begin{cases} 1, if\ \ j^{th}\ parameter\ is\ available\ after\ reduction \\ 0, otherwise \end{cases} \tag{12}$$

$$Min\,Z = \sum_{j=1}^{m} x_j \tag{13}$$

$$r_1 = -2.739x_1 + 0.485x_2 + 8.506x_3 - 6.001x_4 - 1.377x_5 - 6.477x_6 - 2.275x_7 - 1.238x_8 - 1.346x_9 - 0.513x_{10} - 8.966x_{11} \tag{14}$$

$$r_2 = -2.415x_1 + 1.598x_2 + 6.809x_3 - 0.961x_4 + 0.047x_5 - 1.090x_6 - 0.352x_7 - 0.914x_8 - 2.957x_9 + 1.235x_{10} - 5.353x_{11} \tag{15}$$

$$r_3 = 0.620x_1 + 1.598x_2 + 4.018x_3 - 4.803x_4 + 0.047x_5 - 3.013x_6 - 0.850x_7 + 0.511x_8 - 2.957x_9 - 0.189x_{10} - 3.164x_{11} \tag{16}$$

$$r_4 = 2.696x_1 - 5.513x_2 - 3.446x_3 - 4.101x_4 - 5.273x_5 - 3.013x_6 + 8.170x_7 - 1.941x_8 + 6.063x_9 - 4.732x_{10} - 2.403x_{11} \tag{17}$$

$$r_5 = -0.991x_1 + 4.217x_2 - 1.042x_3 - 4.533x_4 - 1.377x_5 + 0.023x_6 + 0.761x_7 + 2.122x_8 + 5.257x_9 - 0.481x_{10} - 1.290x_{11} \tag{18}$$

$$r_6 = -2.415x_1 - 1.850x_2 - 2.727x_3 - 4.101x_4 - 2.097x_5 + 0.023x_6 - 5.739x_7 - 0.914x_8 + 5.827x_9 + 1.734x_{10} - 2.901x_{11} \tag{19}$$

$$r_7 = 3.992x_1 + 4.310x_2 - 0.804x_3 - 0.637x_4 + 6.518x_5 + 1.575x_6 + 3.380x_7 + 3.675x_8 - 1.346x_9 + 2.847x_{10} + 3.817x_{11} \tag{20}$$

$$r_8 = 8.817x_1 + 8.034x_2 - 4.208x_3 + 10.132x_4 + 7.218x_5 + 7.756x_6 + 6.321x_7 + 9.531x_8 + 5.090x_9 + 10.484x_{10} + 7.110x_{11} \tag{21}$$

$$r_9 = -6.311x_1 - 6.078x_2 - 3.754x_3 + 6.108x_4 - 2.003x_5 + 1.575x_6 - 2.599x_7 - 5.753x_8 - 8.925x_9 - 4.829x_{10} + 6.802x_{11} \tag{22}$$

$$r_{10} = -1.254x_1 - 6.802x_2 - 3.352x_3 + 8.899x_4 - 1.702x_5 + 2.642x_6 - 6.818x_7 - 5.080x_8 - 4.706x_9 - 5.553x_{10} + 6.347x_{11} \tag{23}$$

$$\begin{cases} r_8 - r_7 > 0 \\ r_7 - r_5 > 0 \\ r_5 - r_2 > 0 \\ r_2 - r_3 > 0 \\ r_3 - r_4 > 0 \\ r_4 - r_6 > 0 \\ r_6 - r_{10} > 0 \\ r_{10} - r_1 > 0 \\ r_1 - r_9 > 0 \end{cases} \tag{24}$$

$$x_j = \{0,1\},\ j = 1,2,...,11 \tag{25}$$

$$r_i = A real\ number, i = 1,2,...,10 \tag{26}$$

Following the implementation of parameter reduction, the results are presented in Table 8. The findings indicate that utilizing criteria except CIR1, CIR2 and CIR6 for evaluation alters the ranking of the alternatives.

Table 8. The result of optimization based approach

x_1	x_2	x_3	x_4	x_5	x_6
0	0	1	1	1	0
x_7	x_8	x_9	x_{10}	x_{11}	
1	1	1	1	1	
r_1	r_2	r_3	r_4	r_5	
-13.21	-2.45	-7.39	-7.66	-0.58	
r_6	r_7	r_8	r_9	r_{10}	
-10.92	17.45	51.68	-14.95	-11.97	

This study further employs the method introduced by Qin et al., which involves the use of a threshold value to compare pairs of parameters [14]. In the present work, the threshold was set at 1.545. Unlike the original method, this study incorporates a distance measure based on qROF numbers to evaluate the differences between parameters. The results obtained through this modified approach are presented in Table 9. The results show that one of CIR1 and CIR2, one of CIR1 and CIR5, one of CIR1 and CIR7, one of CIR1 and CIR8, one of CIR1 and CIR10, one

of CIR2 and CIR5, one of CIR2 and CIR8, one of CIR2 and CIR10, one of CIR5 and CIR7, one of CIR5 and CIR8, one of CIR5 and CIR10, one of CIR6 and CIR8, one of CIR6 and CIR11, one of CIR7 and CIR8, one of CIR8 and CIR10 can be reduced to evaluate the alternative without changing the rank.

Table 9. qROF number based distance measurement approach

	CIR1-2	CIR1-3	CIR1-4	CIR1-5	CIR1-6	CIR1-7	CIR1-8	CIR1-9	CIR1-10	CIR1-11	CIR2-3
Distance	1.488	2.655	2.810	1.217	1.699	1.379	0.949	1.924	1.493	2.039	2.555
λ	1	0	0	1	0	1	1	0	1	0	0
	CIR2-4	CIR2-5	CIR2-6	CIR2-7	CIR2-8	CIR2-9	CIR2-10	CIR2-11	CIR3-4	CIR3-5	CIR3-6
Distance	3.260	1.229	2.159	1.627	0.879	2.124	1.032	2.996	4.082	2.388	3.099
λ	0	1	0	0	1	0	1	0	0	0	0
	CIR3-7	CIR3-8	CIR3-9	CIR3-10	CIR3-11	CIR4-5	CIR4-6	CIR4-7	CIR4-8	CIR4-9	CIR4-10
Distance	2.944	2.542	3.385	2.806	4.033	2.391	1.828	3.178	2.719	4.159	2.554
λ	0	0	0	0	0	0	0	0	0	0	0
	CIR4-11	CIR5-6	CIR5-7	CIR5-8	CIR5-9	CIR5-10	CIR5-11	CIR6-7	CIR6-8	CIR6-9	CIR6-10
Distance	1.952	1.685	1.398	1.118	2.431	1.117	2.253	2.040	1.527	2.619	1.779
λ	0	0	1	1	0	1	0	0	1	0	0
	CIR6-11	CIR7-8	CIR7-9	CIR7-10	CIR7-11	CIR8-9	CIR8-10	CIR8-11	CIR9-10	CIR9-11	CIR10-11
Distance	1.268	1.280	1.866	1.830	2.686	2.070	0.806	2.284	2.257	3.461	2.825
λ	1	1	0	0	0	0	1	0	0	0	0

This study integrates the findings from both Table 8 and Table 9. According to Table 8, CIR 3,4,5,7,8,9,10,11 must be included in the evaluation process. Based on this condition, Table 9 offers two alternatives for parameter reduction: one option suggests reducing CIR1 and CIR6, while the other proposes the reduction of CIR2 and CIR6 parameters. Table 9 presents the pairwise distance values calculated between criteria using the proposed qROF-based Minkowski distance approach. The obtained distance values indicate the similarity levels between criteria under the qROF environment. The distance values above threshold value observed between certain criterion pairs indicate stronger discrimination capability and greater contribution to the evaluation process. The integrated interpretation of Table 8 and Table 9 enabled a more systematic parameter reduction mechanism by combining optimization-based ranking preservation with similarity-based redundancy analysis.

4. Discussion

The proposed qROF number based parameter reduction framework offers several advantages for multi-criteria decision-making problems. By integrating optimization-based ranking preservation and distance-based parameter reduction, the framework provides a more systematic and reliable evaluation process. Unlike existing approaches that randomly eliminate similar parameters, the proposed method protects the same ranking of alternatives. In addition, qROF numbers enable more flexible representation of uncertain expert evaluations compared to classical fuzzy structures. The framework can also be adapted to different decision-making problems involving many criteria.

However, the proposed approach has some limitations. The reduction results depend on predefined threshold values, and different threshold selections may affect the outcomes. Moreover, the framework was validated using only an electric vehicle battery design application.

5. Conclusion

This study proposed an integrated qROF number-based parameter reduction framework for multi-criteria decision-making problems under uncertain environments. The framework combines optimization-based ranking preservation and qROF-based distance analysis to reduce redundant criteria while maintaining the complete ranking structure of alternatives. In contrast to many existing parameter reduction studies that rely on random elimination or partial ranking consistency, the proposed framework provides a more systematic and reliable reduction mechanism.

The study utilized q-rung orthopair fuzzy numbers to represent uncertain expert evaluations with greater flexibility compared to traditional fuzzy structures. Two successive approaches were integrated within the proposed framework. In the first approach, score values derived from qROF membership and non-membership degrees were incorporated into an optimization model to determine indispensable criteria without changing the ranking order of alternatives. In the second approach, a qROF-based Minkowski distance mechanism was used to identify similar and potentially redundant criteria according to a predefined threshold value.

The applicability and effectiveness of the proposed framework were examined through an electric vehicle battery design problem involving multiple criteria and alternatives. The findings demonstrated that the proposed approach successfully reduced the number of criteria while preserving ranking consistency among alternatives. The integrated evaluation of optimization-based and distance-based analyses enabled a more robust parameter reduction process compared to isolated approaches.

Despite these contributions, the study has several limitations. The reduction results may vary depending on the selected threshold values, and the applicability of the framework was

evaluated using a single application case. In addition, the study focuses on a methodological integration framework rather than the development of a completely new fuzzy algebraic theory or operator structure.

Future studies may extend this work by applying the framework to different decision-making domains and by developing new qROF number-based operators, aggregation mechanisms, and mathematically proof-supported theoretical structures.

Conflict of Interest Statement

The authors declare that there is no conflict of interest in the study.

CRediT Author Statement

Leyla Efe: Conceptualization, Data curation, Writing-original draft, Writing - review & editing,
Burak Efe: Conceptualization, Formal analysis, Methodology, Writing-original draft, Validation, Supervision, Writing - review & editing

Declaration of Generative AI in the Writing Process

The authors declare that no generative AI or AI-assisted technologies were used in the preparation of this manuscript.

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