

Temporal-aware decision modeling for future energy planning based on complex q-rung orthopair fuzzy Aczel–Alsina CRITIC–WASPAS framework

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Abstract: The increasing global demand for energy, environmental concerns, and rapid technological advancements have made future energy planning a challenging multi-criteria decision-making (MCDM) problem. The selection of appropriate energy strategies requires simultaneously considering economic, environmental, technological, and policy-related factors under uncertain and evolving conditions. Conventional MCDM approaches are often inadequate for handling complex uncertainty and temporal variations in decision information. To address these challenges, this study proposes a Temporal-Aware Complex q-Rung Orthopair Fuzzy Aczel–Alsina CRITIC–WASPAS (Cq-ROF-AA-CRITIC–WASPAS) framework for future energy planning. The proposed framework employs Cq-ROFSs to represent uncertain decision information, while the proposed Aczel–Alsina aggregation operators effectively fuse temporal decision matrices by assigning greater importance to recent evaluations. The Criteria Importance Through Intercriteria Correlation (CRITIC) method objectively determines attribute weights by considering contrast intensity and inter-criteria correlation, whereas the Weighted Aggregated Sum Product Assessment (WASPAS) method ranks the energy alternatives through a hybrid additive-multiplicative evaluation strategy. A hypothetical future energy planning case study is presented to demonstrate the applicability of the proposed mathematical model using evaluation criteria related to economic viability, environmental sustainability, technological preparedness, energy security, and policy flexibility. Furthermore, comparative and sensitivity analyses are conducted to evaluate the effectiveness and stability of the proposed framework. The obtained results demonstrate that the proposed framework provides a flexible and systematic approach for handling complex uncertainty and temporal decision information, offering reliable decision support for future energy planning and other uncertain MCDM applications.

Keywords: energy planning; complex q-rung orthopair fuzzy sets; Aczel–Alsina aggregation operators; CRITIC–WASPAS framework

1. Introduction

Energy planning has become a cornerstone of sustainable development, energy security, and long-term economic stability as global energy systems undergo rapid transformation driven by climate change concerns, technological innovation, and

growing energy demand. Modern-day energy planning demands that decision-makers compare various energy options, policy options, and infrastructure investments, and compare the economic efficiency, environmental sustainability, and social acceptability of these in the long term. Making systematic evaluations of future energy strategies in a state of uncertainty has gained more and more importance to policymakers and planners as the rates of energy transition increase across the globe. Although it is important, there is a high level of complexity in the process of choosing the most appropriate future energy planning strategy. Energy substitutes should be evaluated with a set of several contradictory criteria, such as cost-effectiveness, environmental impact, technological maturity, energy security, and policy flexibility. These criteria are very interdependent, and their relative importance over time may vary due to fluctuating regulations, market forces, and technological changes. Moreover, long-term energy planning is an activity that is subjective, inaccurate, and uncertain due to the basis of its knowledge and forecasts. As Prasad et al. [1] pointed out, energy planning is a complex process that cannot be sufficiently presented by standard single-objective or fixed decision-making techniques. The issue of energy planning in the future is also made more problematic by sustainability objectives and time effects. As Aryanpur et al. [2] determined, uncertain demand growth, the proliferation of technologies, and the formation of policies should be considered in energy planning at the national level, particularly when planning to transition to sustainable electricity systems. On the same note, Tsangas et al. [3] highlighted the fact that modern energy planning is working in a radically new space due to the commitment to climate, geopolitical insecurity, and decentralized energy systems, which necessitate adaptive and prospective assessment models. According to these studies, the conventional tools of planning may have difficulties in reflecting the dynamic and unpredictable future of energy systems. Neves et al. [4] enhanced a sustainable and inclusive local energy planning methodology, which emphasizes social and environmental long-term goals. Ferrari et al. [5] evaluated available urban energy planning tools and deemed that most of them cannot incorporate a combination of multiple criteria and uncertainty in a single and open way. These restrictions point to a need for stronger MCDM models that are able to deal with non-homogeneous information and flexible planning situations. Mahbub et al. [6] proposed a multi-objective optimization tool to be used in long-term energy planning and proved it to be effective in balancing economic and environmental goals. Over the last few years, there has been another boost in the field of future energy planning by highlighting sustainable and uncertainty-aware decision strategies. Mohseni and Brent [7] conducted a thorough review of long-term sustainable energy system planning and highlighted the current research trends, optimization methodologies, and future challenges. The energy-climate nexus was also explored by Bogia et al. [8], who emphasized the need for integrated planning solutions that integrate sustainability, climate resilience, and energy security. Moreover, Wiest et al. [9] proposed low-regret planning strategies for very uncertain future energy systems, which show that strong and adaptive decision-support frameworks are necessary for long-term energy planning.

Nevertheless, although optimization models provide good numerical solutions, they usually need accurate input information, and they are less effective in translating expert hesitation, partial data, and uncertainty involved in long-term forecasting. This means that the results of the decisions cannot be very robust in cases where uncertainty is not stated. Fuzzy-based decision-making systems have been widely used to model uncertainty in energy planning problems that comprise traditional fuzzy sets (FSs), intuitionistic fuzzy sets (IFSs), Pythagorean fuzzy sets (PFSs), and q-ROFSs. Though these methods are more effective in representing uncertainty, they are still limited in terms of multidimensional and time-dependent uncertainty and expert judgments that may have complex values. In order to fill this gap, this paper suggests a time-conscious hybrid CRITIC-WASPAS model on the basis of Cq-ROFSs to plan energy in the future. The proposed framework uses complex fuzzy uncertainty representation and objective CRITIC-based weighting coupled with the discriminative ability of WASPAS to produce a reliable, transparent, and useful decision support system to assess and rank future energy planning options in the face of uncertainty.

Study framework

This paper is organized into eight sections. Section 1 introduces the study and motivates a temporal-aware approach for future energy planning. Section 2 reviews relevant literature on fuzzy MCDM and future energy planning. Section 3 formulates the research problem and highlights the contributions of the hybrid CRITIC-WASPAS framework. Section 4 is the development of the key concepts of Cq-ROFSs, and Section 5 develops the Aczel–Alsina aggregation operators. The CRITIC-WASPAS evaluation is discussed in Section 6. Section 7 illustrates comparative analysis with different methods, and Section 8 concludes the research, providing insights and research directions for the future. **Figure 1** presents the study framework.



Figure 1. Study framework.

2. Literature review

MCDM systems based on fuzzy theory have attracted substantial attention due to their ability to handle uncertainty, ambiguity, imprecision, and conflicting expert judgments in complex decision environments. Due to their strategic areas of interest, like renewable energy planning, smart city development, and sustainability assessment, decision-makers are often faced with multidimensional and dynamic uncertainties that are not effectively represented by crisp mathematical models. A combination

of objective weighting techniques like CRITIC with strong ranking techniques like WASPAS has been developed as a potent aid to enhancing discrimination and stability of evaluations. As time has passed, these structures have been developed as FS extensions have increasingly been made more expressive; classical FSs have been developed into IFs, PFSs, q-ROFSs, and finally to complex-valued fuzzy environments able to represent multidimensional uncertainty structures. A fuzzy-based CRITIC-WASPAS framework was used by Zhou and Yang [10] to determine the critical dimensions in education and instructor training. They showed that objective CRITIC weighting integrated with WASPAS ranking leads to high evaluation reliability through incorporating inter-criteria correlation and contrast intensity. Çolak and Kaya [11] created an integrated fuzzy MCDM model for renewable energy prioritization, the findings of which underscore the role of structured fuzzy assessment in energy planning by country. Dursun and Karsak [12] suggested a fuzzy MCDM model to use in the selection of personnel, whereas Tsaur et al. [13] used fuzzy MCDM in the evaluation of the quality of airline services. These early research works validated the idea that fuzzy-based systems were useful to handle linguistic and subjective data, although restricted to a single-dimensional representation of uncertainty. In order to develop uncertainty modeling better, IF environments were proposed, which feature membership and non-membership degrees. Deb et al. [14] came up with an IF consensus WASPAS technique that assesses open-source learning management systems, which enhances discrimination amid uncertain information. Another article that mentioned Aczel–Alsina aggregation operators to support IF MCDM was introduced by Senapati et al. [15] with the intention to enhance the adaptability and sensitivity of the aggregation. An additional extension of CRITIC-WASPAS to continuous IF was made by Alkan and Kahraman [16] in the evaluation of smart cities. Fahmi et al. [17] developed circular IF Hamacher aggregation operators and successfully applied them to MADM problems, with a flexible framework for dealing with complex uncertainty and interactions among the decision information. Wang et al. [18] proposed the Aczel–Alsina power aggregation operators for intuitionistic hesitant fuzzy environment based on Aczel–Alsina t-norm and t-conorm. Their method was found to contribute to the aggregation of reluctant information and to be successfully applied to the selection of logistics service providers. Although these contributions improved uncertainty representation, the linear constraint of IFS still restricts higher-order modeling capacity. This limitation was overcome by PFSs, which softened the membership-non-membership constraint, adding more expressiveness. Lai and Chang [19] developed a new group decision-making approach under the heterogeneous information by using SWARA method with PF approach. The proposed framework includes new scores and accuracy functions to treat incomplete, hesitant and uncertain information in complex decision making problems effectively. Haq et al. [20] incorporated the PF Aczel–Alsina operators into an assessment decision model using the closeness coefficient in investment policy evaluation. Hussain et al. [21] proposed new Aczel–Alsina operators of PFSs that increase the efficiency of the aggregation, whereas Hussain et al. [22] suggested new operators of PF Aczel–Alsina Hamy means that can capture interdependencies between attributes.

Gurmani et al. [23] proposed linguistic PF Aczel–Alsina aggregation operators used for MADM. Their approach was a successful modelization of linguistic uncertainty and was successfully transferred to the development of smart cities, which resulted in an enhancement in their aggregation capability and decision-making performance. A disaster decision-making framework using Fermatean fuzzy numbers and the mixing regret philosophy DDAS method was presented by Fahmi et al. [24], which was effective in ranking the alternatives in complex and uncertain decision-making environments. Although better balanced, PFS frameworks still have quadratic constraints, which might limit attempts to model extreme hesitation. The introduction of q-ROFSs significantly enhanced uncertainty modeling by generalizing IFS and PFS through the q^{th} power condition. Khan et al. [25] used q-ROF Aczel–Alsina aggregation operators to select construction material, which has a better expressive capacity than the previous fuzzy extensions. Ali et al. [26] presented generalized q-ROF Aczel–Alsina operators and applied them to wireless sensor networks, providing a demonstration of strength in terms of multidimensional expert evaluations. In the study by Senapati et al. [27], the global partner selection involved the q-ROF Aczel–Alsina average operator. Ali et al. [28] introduced aggregation operators for q-rung orthopair neutrosophic soft sets and applied these operators to the MADM problems, proving their ability to handle uncertain and indeterminate information and express decision flexibility. For addressing investment decision-making problems under uncertainty, Rahim et al. [29] introduced cosine similarity and distance measures for p,q-quasirung fuzzy sets and showed the usefulness of advanced fuzzy structures for uncertainty representation and alternative evaluation. To solve the sustainable supplier selection problem under the p,q-quasirung orthopair fuzzy environment, Ali et al. [30] proposed prioritized Aczel–Alsina aggregation operators, which offer better flexibility and effectiveness in MCDM with uncertainty. These investigations show that q-ROFSs introduce increased flexibility and power of discrimination in intricate MCDM issues. Nevertheless, although such theoretical progress has been made, the vast majority of currently available CRITIC-WASPAS and aggregation-based frameworks are real-valued and static. They mainly represent unidimensional uncertainty, but do not represent multidimensional uncertainty, which defines the energy planning conditions in the future. The importance of criteria and alternative performance changes over time in the formulation of energy strategies in the long term as a result of technological innovation, changes in policy, variability in the economy, and environmental dynamics. Such complex and time-dependent forms of uncertainty cannot be fully contained by real-valued q-ROFS frameworks. This restriction underscores the need to extend q-ROFSs to the complex-valued environment, where both membership degrees and non-membership degrees will be complex numbers, which will accommodate multidimensional uncertainty. The flexible parameterized Aczel–Alsina aggregation operators are used to effectively aggregate such complex information, offering more flexibility in modeling uncertain decision information. In addition, the CRITIC method is used to objectively determine the weights of criteria based on both contrast intensity and inter-criteria correlation, and the capabilities of reliable and discriminative ranking by the introduction of weighted sum and weighted

product models are used in the WASPAS method. The proposed model combines the Cq-ROFSs and Aczel–Alsina operators with the hybrid CRITIC-WASPAS framework; thus, the model is simultaneously able to consider multidimensional uncertainty, temporal information, and objective decision preferences. Therefore, the proposed Temporal-Aware Decision Framework is able to model uncertainty, aggregate uncertainty in a flexible manner, provide an objective weighting for uncertainty, and rank uncertainty systematically in one framework, thus bridging an important research gap for future energy planning.

3. Research problem

Energy planning has now taken a very crucial and strategic role in sustainable development as it allows policymakers and planners to analyze energy technologies, optimize energy portfolios, and make well-informed decisions regarding the proposed energy systems in the future. These plans can be applied to ensure renewable energy sources, reduce carbon emissions, and enhance energy security, taking into consideration the economic, technological, and environmental factors. Nevertheless, the decision on the most suitable energy planning strategy is an extremely complex process. Assessments should consider several, even competing, factors, such as financial viability, environmental effects, technical feasibility, reliability, social acceptability, and suitability to changing energy needs. This is complicated further by uncertainty, incompleteness, and ambiguity because of variability of energy data, the heterogeneity of regional energy systems, and the subjectivity of expert judgments. The conventional MCDM techniques and simple fuzzy systems cannot handle the multidimensional and other higher-order uncertainties of energy planning. State-of-the-art fuzzy systems are offered using more advanced fuzzy models, including intuitionistic, Pythagorean, and q-ROFSs, which offer the capability of modeling both membership and non-membership information, but cannot effectively model sophisticated expert judgments, criterion interdependencies, and energy system dynamics in the future. In order to overcome these shortcomings, this paper tends to suggest a temporal-conscious Cq-ROF-CRITIC-WASPAS-based energy planning. The structure of the systematized assessment and ranking of energy planning choices is based on the representation of expert opinions as complex-valued membership and non-membership attributes, giving the chance of a more realistic and expressive modeling of uncertainty. The CRITIC method objectively calculates criterion weights, taking into account contrast as well as interdependence, whereas the WASPAS method gives strong and discriminatory rankings as a result of combining additive and multiplicative utility measures. The existing MCDM applications have potential as well as limitations, which are captured in the recent literature. Kaya and Kahraman [31] used the modified fuzzy TOPSIS method, which enhanced decision-making under uncertainty but used unidimensional fuzzy data. Abdullah and Najib [32] applied IF AHP to the selection of sustainable energy technology but found the model inadequate in modeling the interdependent criteria and multidimensional uncertainty. As reported by Cajot et al. [33], the city energy system is highly complex because the

conventional method can hardly embrace changes over time and subjective decisions. Diakoulaki et al. [34] addressed the application of MCDA in energy planning and expressed its significance in solving conflicting objectives and the various evaluation criteria. The study was a comprehensive overview of the MCDA approaches for supporting strategic energy-related decision making. Hussain et al. [21] proposed new Aczel–Alsina aggregation operators in a PF setting and used these operators in MADM problems. The proposed operators increased the flexibility in information aggregation in uncertain and complex decision scenarios. Khan et al. [25] introduced a q-ROF MCDM model for construction material selection based on the Aczel–Alsina aggregation. The method is able to address higher-order uncertainty by using q-ROF information and advanced aggregation operators. But these schemes are still weak in the areas of higher-order uncertainties and multifaceted preferences of stakeholders.

Critical analysis of these studies shows that there are several gaps in the research:

- The existing MCDM models of energy planning are not able to adequately model the multidimensional and Cq-ROF uncertainty in expert judgments.
- The flexible q-R framework that allows independent modeling of membership and non-membership data is not being well exploited in energy alternatives evaluation.
- The interdependence between such critical criteria as cost, environmental influence, reliability, and technological feasibility is not taken into consideration, and suboptimal prioritization is made.
- Existing ranking mechanisms offer partial discrimination and strength in cases where energy alternatives behave in the same manner across unpredictable, variable, and time-varying situations.

To address these shortcomings, the present study introduces a temporal-aware Cq-ROF-CRITIC-WASPAS framework, which can incorporate multidimensional uncertainty and expert opinions, as well as offer an exceptionally discriminative, transparent, and robust evaluation system. The framework will ensure reliable and better-informed decision-making in energy planning by aiding in the process of making sustainable and efficient energy strategies in case of future scenarios. The characteristic comparison is given in **Table 1**.

Table 1. Characteristic comparison.

Characteristics	Kaya and Kahraman [31]	Abdullah and Najib [32]	Cajot et al. [33]	Diakoulaki et al. [34]	Hussain et al. [21]	Khan et al. [25]	Proposed study
Fuzzy Environment	FS	IFS	MCDA	MCDA	PFS	q - ROFS	Cq - ROFS
Handles Multidimensional Uncertainty	No	Partially	No	No	Yes	Yes	Yes
Flexible Membership/Non-Membership Modeling	Limited	Yes	No	No	Yes	Yes	Yes
Models Interdependent Criteria	Partially	Partially	Yes	Yes	Partially	Partially	Yes
Incorporates Temporal Dynamics	No	No	Partially	No	No	No	Yes
Objective Criteria Weight Determination	No	Yes	No	Partially	No	No	Yes
Advanced Aggregation Capability	No	No	No	No	Yes	Yes	Yes
Robust Ranking	Yes	Yes	Yes	Yes	Yes	Yes	Yes

A comparison of characteristics of existing theories vs. proposed work is shown in **Figure 2**.



Figure 2. Comparison of characteristics with different theories.

Contributions

The evaluation and ranking of energy planning alternatives are critically challenged by multidimensional, interdependent, and conflicting uncertainties inherent in expert judgments. Such uncertainties may also not be well manifested in the current ways, limiting the reliability, robustness, and interpretability of the assessments. Due to these deficiencies, this paper proposes a time-dependent Cq-ROF-CRITIC-WASPAS model, which offers a structured, uncertain, and evidence-based plan for ranking energy planning plans.

The novelty of this study is the development of a Temporal-Aware Cq-ROF Aczel–Alsina CRITIC-WASPAS framework for energy planning under uncertainty in the future. Unlike conventional MCDM approaches that perform evaluations at a single time period, the proposed framework incorporates multiple temporal decision matrices through a temporal weighting mechanism, allowing recent assessments to receive greater importance. Moreover, the proposed aggregation operators Aczel–Alsina are combined with the CRITIC objective weighting method and the ranking method WASPAP in order to create a unified and flexible decision-making framework that is

able to tackle Cq-ROF information.

The most important findings of the study are:

(1) Development of advanced Cq-ROF aggregation operators

- Complex q-rung orthopair fuzzy Aczel–Alsina weighted average (Cq-ROFAAWA) operators.
- Complex q-rung orthopair fuzzy Aczel–Alsina weighted geometric (Cq-ROFAAWG) operators.

(2) Systematic, objective, and uncertainty-conscious prioritization of energy alternatives

The framework is a combination of Cq-ROF operators, the CRITIC weighting method, and the WASPAS ranking method to ensure that interdependencies amongst criteria are taken into account and that the outcomes of the rankings are sound, discriminative, and reflect expert preferences.

(3) Practical applicability in sustainable energy planning

The suggested framework is applied to the real-life situation of energy planning, and it is shown that it will assist policymakers and other planners in choosing the most appropriate energy strategies amidst multidimensional uncertainty and changing energy requirements.

(4) Comparative validation against existing methods

Comprehensive comparisons to the classical fuzzy, IF, and other MCDM models prove that the proposed Cq-ROF-CRITIC-WASPAS framework is more robust, discriminative, stable, and reliable, as opposed to the existing approaches. The findings show that it is a powerful decision-support tool, which facilitates the assessment and prioritization of energy options to enhance strategic and operational choices in sustainable energy planning.

Key contributions are shown in **Figure 3**.

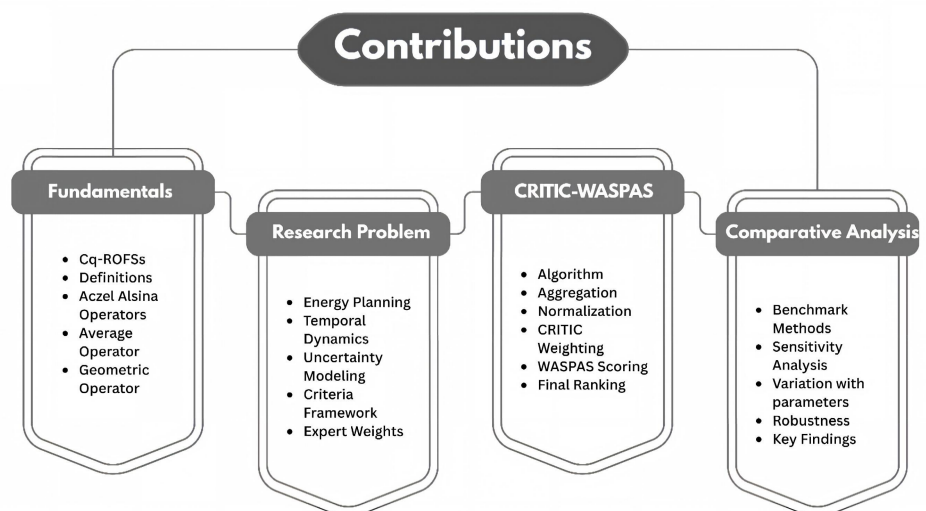


Figure 3. Contributions of proposed work.

4. Fundamentals

Definition 1 ([35]). Given a universal set $\mathcal{U}$, the Cq-ROFS B is defined on $\mathcal{U}$ as:

$$B = \left\{ \left(\hbar, \overline{M}^{\widehat{m}}, \overline{N}^{\widehat{m}} \right) | \hbar \in \mathcal{U} \right\} = \left\{ \left(\hbar, \overline{M}^{\widehat{m-re}} + {}_{\iota}\overline{M}^{\widehat{m-im}}, \overline{N}^{\widehat{m-re}} + {}_{\iota}\overline{N}^{\widehat{m-im}} \right) | \hbar \in \mathcal{U} \right\} \quad (1)$$

Where $\overline{M}^{\widehat{m}} : \mathcal{U} \rightarrow [0, 1]$ and $\overline{N}^{\widehat{m}} : \mathcal{U} \rightarrow [0, 1]$ denote the membership and non-membership functions satisfying the following condition:

$$0 \leq \left(\overline{M}^{\widehat{m-re}} \right)^{\tilde{q}} + \left(\overline{N}^{\widehat{m-re}} \right)^{\tilde{q}} \leq 1 \text{ and } 0 \leq \left(\overline{M}^{\widehat{m-im}} \right)^{\tilde{q}} + \left(\overline{N}^{\widehat{m-im}} \right)^{\tilde{q}} \leq 1$$

Where, $\tilde{q} \geq 1$.

Definition 2 ([35]). For a Cq-ROFN $B = \left(\overline{M}^{\widehat{m-re}} + {}_{\iota}\overline{M}^{\widehat{m-im}}, \overline{N}^{\widehat{m-re}} + {}_{\iota}\overline{N}^{\widehat{m-im}} \right)$. Then the score and accuracy measures are obtained as follows:

$$\begin{aligned} S(B) &= \frac{1}{4} \left\{ 2 + \left(\overline{M}^{\widehat{m-re}} \right)^{\tilde{q}} + \left(\overline{M}^{\widehat{m-im}} \right)^{\tilde{q}} - \left(\overline{N}^{\widehat{m-re}} \right)^{\tilde{q}} - \left(\overline{N}^{\widehat{m-im}} \right)^{\tilde{q}} \right\} \\ A(B) &= \frac{1}{4} \left\{ 2 + \left(\overline{M}^{\widehat{m-re}} \right)^{\tilde{q}} + \left(\overline{M}^{\widehat{m-im}} \right)^{\tilde{q}} + \left(\overline{N}^{\widehat{m-re}} \right)^{\tilde{q}} + \left(\overline{N}^{\widehat{m-im}} \right)^{\tilde{q}} \right\}. \end{aligned}$$

Definition 3 ([36]). For $\mathfrak{b}_1, \mathfrak{b}_2 \in [0, 1]$ and $\kappa \geq 1$, the Aczel–Alsina t -norm and t -conorm can be defined as:

$$\begin{aligned} T^{\widehat{N}}(\mathfrak{b}_1, \mathfrak{b}_2) &= e^{(-((- \ln \mathfrak{b}_1)^{\kappa} + (- \ln \mathfrak{b}_2)^{\kappa})^{\frac{1}{\kappa}})} \\ T^{\widehat{S}}(\mathfrak{b}_1, \mathfrak{b}_2) &= 1 - e^{(-((- \ln(1 - \mathfrak{b}_1))^{\kappa} + (- \ln(1 - \mathfrak{b}_2))^{\kappa})^{\frac{1}{\kappa}})}. \end{aligned}$$

Definition 4. Let $B = \left(\overline{M}^{\widehat{m-re}} + {}_{\iota}\overline{M}^{\widehat{m-im}}, \overline{N}^{\widehat{m-re}} + {}_{\iota}\overline{N}^{\widehat{m-im}} \right)$, $B_1 = \left(\overline{M}_1^{\widehat{m-re}} + {}_{\iota}\overline{M}_1^{\widehat{m-im}}, \overline{N}_1^{\widehat{m-re}} + {}_{\iota}\overline{N}_1^{\widehat{m-im}} \right)$ and $B_2 = \left(\overline{M}_2^{\widehat{m-re}} + {}_{\iota}\overline{M}_2^{\widehat{m-im}}, \overline{N}_2^{\widehat{m-re}} + {}_{\iota}\overline{N}_2^{\widehat{m-im}} \right)$ and be Cq-ROFNs and $\kappa \geq 1, \lambda > 0$, then

Aczel–Alsina operations based on t -norm and t -conorm for Cq-ROFNs are defined as:

$$\begin{aligned}
 1. \quad B_1 \oplus B_2 &= \left(\begin{aligned} &\sqrt[\bar{q}]{1-e \left(- \left(\left(-\ln \left(1 - \left(\overline{M_1^m - re} \right)^{\bar{q}} \right) \right)^{\kappa} + \left(-\ln \left(1 - \left(\overline{M_2^m - re} \right)^{\bar{q}} \right) \right)^{\kappa} \right)^{\frac{1}{\kappa}}} + \\ &\sqrt[\bar{q}]{1-e \left(- \left(\left(-\ln \left(1 - \left(\overline{M_1^m - im} \right)^{\bar{q}} \right) \right)^{\kappa} + \left(-\ln \left(1 - \left(\overline{M_2^m - im} \right)^{\bar{q}} \right) \right)^{\kappa} \right)^{\frac{1}{\kappa}}} + \\ &e \left(\left(-\ln \left(\overline{N_1^m - re} \right) \right)^{\kappa} + \left(-\ln \left(\overline{N_2^m - re} \right) \right)^{\kappa} \right)^{\frac{1}{\kappa}} + \\ &\iota e \left(\left(-\ln \left(\overline{N_1^m - im} \right) \right)^{\kappa} + \left(-\ln \left(\overline{N_2^m - im} \right) \right)^{\kappa} \right)^{\frac{1}{\kappa}} \end{aligned} \right); \\
 2. \quad B_1 \otimes B_2 &= \left(\begin{aligned} &e \left(\left(-\ln \left(\overline{M_1^m - re} \right) \right)^{\kappa} + \left(-\ln \left(\overline{M_2^m - re} \right) \right)^{\kappa} \right)^{\frac{1}{\kappa}} + \\ &\iota e \left(\left(-\ln \left(\overline{M_1^m - im} \right) \right)^{\kappa} + \left(-\ln \left(\overline{M_2^m - im} \right) \right)^{\kappa} \right)^{\frac{1}{\kappa}} + \\ &\sqrt[\bar{q}]{1-e \left(\left(-\ln \left(1 - \left(\overline{N_1^m - re} \right)^{\bar{q}} \right) \right)^{\kappa} + \left(-\ln \left(1 - \left(\overline{N_2^m - re} \right)^{\bar{q}} \right) \right)^{\kappa} \right)^{\frac{1}{\kappa}}} + \\ &\sqrt[\bar{q}]{1-e \left(\left(-\ln \left(1 - \left(\overline{N_1^m - im} \right)^{\bar{q}} \right) \right)^{\kappa} + \left(-\ln \left(1 - \left(\overline{N_2^m - im} \right)^{\bar{q}} \right) \right)^{\kappa} \right)^{\frac{1}{\kappa}}} \end{aligned} \right); \\
 3. \quad \lambda B &= \left(\begin{aligned} &\sqrt[\bar{q}]{1-e \left(\lambda \left(-\ln \left(1 - \left(\overline{M^m - re} \right)^{\bar{q}} \right) \right)^{\kappa} \right)^{\frac{1}{\kappa}}} + \\ &\sqrt[\bar{q}]{1-e \left(\lambda \left(-\ln \left(1 - \left(\overline{M^m - im} \right)^{\bar{q}} \right) \right)^{\kappa} \right)^{\frac{1}{\kappa}}} + \\ &e^{-\left(\lambda \left(-\ln \left(\overline{N^m - re} \right) \right)^{\kappa} \right)^{\frac{1}{\kappa}}} + \iota e^{-\left(\lambda \left(-\ln \left(\overline{N^m - im} \right) \right)^{\kappa} \right)^{\frac{1}{\kappa}}} \end{aligned} \right); \\
 4. \quad B^\lambda &= \left(\begin{aligned} &e^{-\left(\lambda \left(-\ln \left(\overline{M^m - re} \right) \right)^{\kappa} \right)^{\frac{1}{\kappa}}} + \iota e^{-\left(\lambda \left(-\ln \left(\overline{M^m - im} \right) \right)^{\kappa} \right)^{\frac{1}{\kappa}}} + \\ &\sqrt[\bar{q}]{1-e \left(\lambda \left(-\ln \left(1 - \left(\overline{N^m - re} \right)^{\bar{q}} \right) \right)^{\kappa} \right)^{\frac{1}{\kappa}}} + \\ &\sqrt[\bar{q}]{1-e \left(\lambda \left(-\ln \left(1 - \left(\overline{N^m - im} \right)^{\bar{q}} \right) \right)^{\kappa} \right)^{\frac{1}{\kappa}}} \end{aligned} \right).
 \end{aligned}$$

5. Aczel–Alsina aggregation operators based on Cq-ROFSs

Definition 5. Let $B_x = (\overline{M_x^m}, \overline{N_x^m}) = \left(\overline{M_x^m - re} + \iota \overline{M_x^m - im}, \overline{N_x^m - re} + \iota \overline{N_x^m - im} \right)$ ($x = 1, 2, \dots, m$) represent a collection of Cq-ROFNs. Accordingly, the Cq-ROFAAWA operator is expressed as:

$$Cq-ROFAAWA(B_1, B_2, \dots, B_m) = \sum_{x=1}^m (\bar{w}_x B_x) \quad (2)$$

Where, $\bar{w} = (\bar{w}_1, \bar{w}_2, \bar{w}_3, \dots, \bar{w}_m)$ is the associated weight vector subject to conditions

$$0 \leq \bar{w}_x \leq 1 \text{ and } \sum_{x=1}^m \bar{w}_x = 1.$$

Theorem 1. Utilizing the proposed aggregation operator in Equation (2) ensures that the aggregated result retains the Cq-ROFN form. Furthermore,

$$Cq - ROFAAWA(B_1, B_2, \dots, B_m) \\ = \left(\sqrt[q]{1 - e^{-\left\{ \sum_{x=1}^m \left(\left(\bar{w}_x (-\ln(1 - (\overline{M}_x^m - re)^{\frac{\bar{q}}{\kappa}})^{\frac{1}{\kappa}}) \right) \right) \right\}}} + \iota \sqrt[q]{1 - e^{-\left\{ \sum_{x=1}^m \left(\left(\bar{w}_x (-\ln(1 - (\overline{M}_x^m - im)^{\frac{\bar{q}}{\kappa}})^{\frac{1}{\kappa}}) \right) \right) \right\}}} \right), \\ e^{-\left\{ \sum_{x=1}^m \left(\left(\bar{w}_x (-\ln(\overline{N}_x^m - re)^{\frac{\kappa}{\kappa}}) \right) \right) \right\}} + \iota e^{-\left\{ \sum_{x=1}^m \left(\left(\bar{w}_x (-\ln(\overline{N}_x^m - im)^{\frac{\kappa}{\kappa}}) \right) \right) \right\}} \right).$$

Proof. By using the mathematical induction rule.

(i) Let $m = 2$. Then

$$Cq - ROFAAWA(B_1, B_2) = \bar{w}_1 B_1 \oplus \bar{w}_2 B_2 \\ = \left(\left(\sqrt[q]{1 - e^{-\left(\bar{w}_1 \left(-\ln \left(1 - \left(\overline{M}_1^m - re \right)^{\frac{\bar{q}}{\kappa}} \right) \right)^{\frac{1}{\kappa}}}} + \iota \sqrt[q]{1 - e^{-\left(\bar{w}_1 \left(-\ln \left(1 - \left(\overline{M}_1^m - im \right)^{\frac{\bar{q}}{\kappa}} \right) \right)^{\frac{1}{\kappa}}}} \right), \right. \\ \left. e^{-\left(\bar{w}_1 \left(-\ln \left(\overline{N}_1^m - re \right)^{\frac{\kappa}{\kappa}} \right) \right)} + \iota e^{-\left(\bar{w}_1 \left(-\ln \left(\overline{N}_1^m - im \right)^{\frac{\kappa}{\kappa}} \right) \right)} \right) \oplus \\ \left(\sqrt[q]{1 - e^{-\left(\bar{w}_2 \left(-\ln \left(1 - \left(\overline{M}_2^m - re \right)^{\frac{\bar{q}}{\kappa}} \right) \right)^{\frac{1}{\kappa}}}} + \iota \sqrt[q]{1 - e^{-\left(\bar{w}_2 \left(-\ln \left(1 - \left(\overline{M}_2^m - im \right)^{\frac{\bar{q}}{\kappa}} \right) \right)^{\frac{1}{\kappa}}}} \right), \right. \\ \left. e^{-\left(\bar{w}_2 \left(-\ln \left(\overline{N}_2^m - re \right)^{\frac{\kappa}{\kappa}} \right) \right)} + \iota e^{-\left(\bar{w}_2 \left(-\ln \left(\overline{N}_2^m - im \right)^{\frac{\kappa}{\kappa}} \right) \right)} \right) \\ = \left(\sqrt[q]{1 - e^{-\left\{ \sum_{x=1}^2 \left(\left(\bar{w}_x \left(-\ln \left(1 - \left(\overline{M}_x^m - re \right)^{\frac{\bar{q}}{\kappa}} \right) \right)^{\frac{1}{\kappa}} \right) \right\}}} + \iota \sqrt[q]{1 - e^{-\left\{ \sum_{x=1}^2 \left(\left(\bar{w}_x \left(-\ln \left(1 - \left(\overline{M}_x^m - im \right)^{\frac{\bar{q}}{\kappa}} \right) \right)^{\frac{1}{\kappa}} \right) \right\}}} \right), \right. \\ \left. e^{-\left\{ \sum_{x=1}^2 \left(\left(\bar{w}_x \left(-\ln \left(\overline{N}_x^m - re \right)^{\frac{\kappa}{\kappa}} \right) \right) \right\}} + \iota e^{-\left\{ \sum_{x=1}^2 \left(\left(\bar{w}_x \left(-\ln \left(\overline{N}_x^m - im \right)^{\frac{\kappa}{\kappa}} \right) \right) \right\}} \right).$$

Hence, the result is true for $m = 2$.

(ii) Now suppose that the result is true for $m = g$

$$Cq - ROFAAWA(B_1, B_2, \dots, B_g) \\ = \left(\sqrt[q]{1 - e^{-\left\{ \sum_{x=1}^g \left(\left(\bar{w}_x \left(-\ln \left(1 - \left(\overline{M}_x^m - re \right)^{\frac{\bar{q}}{\kappa}} \right) \right)^{\frac{1}{\kappa}} \right) \right\}}} + \iota \sqrt[q]{1 - e^{-\left\{ \sum_{x=1}^g \left(\left(\bar{w}_x \left(-\ln \left(1 - \left(\overline{M}_x^m - im \right)^{\frac{\bar{q}}{\kappa}} \right) \right)^{\frac{1}{\kappa}} \right) \right\}}} \right), \right. \\ \left. e^{-\left\{ \sum_{x=1}^g \left(\left(\bar{w}_x \left(-\ln \left(\overline{N}_x^m - re \right)^{\frac{\kappa}{\kappa}} \right) \right) \right\}} + \iota e^{-\left\{ \sum_{x=1}^g \left(\left(\bar{w}_x \left(-\ln \left(\overline{N}_x^m - im \right)^{\frac{\kappa}{\kappa}} \right) \right) \right\}} \right).$$

Now for $m = g + 1$

$$\begin{aligned}
 & Cq - ROFAAWA(B_1, B_2, \dots, B_g, B_{g+1}) = \sum_{x=1}^g (\bar{w}_x B_x) \oplus \bar{w}_{g+1} B_{g+1} \\
 &= \left(\left(\sqrt[q]{1-e} \left\{ -\sum_{x=1}^g \left(\bar{w}_x \left(-\ln \left(1 - \left(\overline{M}_x^{\overline{m-re}} \right)^{\bar{q}} \right)^{\kappa} \right)^{\frac{1}{\kappa}} \right) \right\} + \iota \sqrt[q]{1-e} \left\{ -\sum_{x=1}^g \left(\bar{w}_x \left(-\ln \left(1 - \left(\overline{M}_x^{\overline{m-im}} \right)^{\bar{q}} \right)^{\kappa} \right)^{\frac{1}{\kappa}} \right) \right\} \right), \right. \\
 & \quad \left. e \left\{ -\sum_{x=1}^g \left(\bar{w}_x \left(-\ln \left(\overline{N}_x^{\overline{m-re}} \right)^{\kappa} \right)^{\frac{1}{\kappa}} \right) \right\} + \iota e \left\{ -\sum_{x=1}^g \left(\bar{w}_x \left(-\ln \left(\overline{N}_x^{\overline{m-im}} \right)^{\kappa} \right)^{\frac{1}{\kappa}} \right) \right\} \right) \oplus \\
 & \quad \left(\sqrt[q]{1-e} \left\{ -\left(\bar{w}_{g+1} \left(-\ln \left(1 - \left(\overline{M}_{g+1}^{\overline{m-re}} \right)^{\bar{q}} \right)^{\kappa} \right)^{\frac{1}{\kappa}} \right) \right\} + \iota \sqrt[q]{1-e} \left\{ -\left(\bar{w}_{g+1} \left(-\ln \left(1 - \left(\overline{M}_{g+1}^{\overline{m-im}} \right)^{\bar{q}} \right)^{\kappa} \right)^{\frac{1}{\kappa}} \right) \right\} \right), \right. \\
 & \quad \left. e \left\{ -\left(\bar{w}_{g+1} \left(-\ln \left(\overline{N}_{g+1}^{\overline{m-re}} \right)^{\kappa} \right)^{\frac{1}{\kappa}} \right) \right\} + \iota e \left\{ -\left(\bar{w}_{g+1} \left(-\ln \left(\overline{N}_{g+1}^{\overline{m-im}} \right)^{\kappa} \right)^{\frac{1}{\kappa}} \right) \right\} \right) \right) \\
 &= \left(\sqrt[q]{1-e} \left\{ -\sum_{x=1}^{g+1} \left(\bar{w}_x \left(-\ln \left(1 - \left(\overline{M}_x^{\overline{m-re}} \right)^{\bar{q}} \right)^{\kappa} \right)^{\frac{1}{\kappa}} \right) \right\} + \iota \sqrt[q]{1-e} \left\{ -\sum_{x=1}^{g+1} \left(\bar{w}_x \left(-\ln \left(1 - \left(\overline{M}_x^{\overline{m-im}} \right)^{\bar{q}} \right)^{\kappa} \right)^{\frac{1}{\kappa}} \right) \right\} \right), \right. \\
 & \quad \left. e \left\{ -\sum_{x=1}^{g+1} \left(\bar{w}_x \left(-\ln \left(\overline{N}_x^{\overline{m-re}} \right)^{\kappa} \right)^{\frac{1}{\kappa}} \right) \right\} + \iota e \left\{ -\sum_{x=1}^{g+1} \left(\bar{w}_x \left(-\ln \left(\overline{N}_x^{\overline{m-im}} \right)^{\kappa} \right)^{\frac{1}{\kappa}} \right) \right\} \right)
 \end{aligned}$$

Hence, the result is true for all positive integers m .

□

Theorem 2. (Idempotency Property). Let $B_x = (\overline{M}_x^{\overline{m}}, \overline{N}_x^{\overline{m}}) = \left(\overline{M}_x^{\overline{m-re}} + \iota \overline{M}_x^{\overline{m-im}}, \overline{N}_x^{\overline{m-re}} + \iota \overline{N}_x^{\overline{m-im}} \right)$ ($x = 1, 2, \dots, m$) represent a collection of Cq-ROFNs. If all B_m are identical, i.e., $B_m = B$, then

$$Cq - ROFAAWA(B_1, B_2, \dots, B_m) = B.$$

Theorem 3. (Boundedness Property). Let $B_x = (\overline{M}_x^{\overline{m}}, \overline{N}_x^{\overline{m}}) = \left(\overline{M}_x^{\overline{m-re}} + \iota \overline{M}_x^{\overline{m-im}}, \overline{N}_x^{\overline{m-re}} + \iota \overline{N}_x^{\overline{m-im}} \right)$ ($x = 1, 2, \dots, m$) represent a collection of Cq-ROFNs. If $B^- = \min(B_1, B_2, \dots, B_m)$ and $B^+ = \max(B_1, B_2, \dots, B_m)$, then

$$B^- \leq Cq - ROFAAWA(B_1, B_2, \dots, B_m) \leq B^+.$$

Theorem 4. (Monotonicity Property). Let $B_x = \left(\overline{M}_x^{\overline{m-re}} + \iota \overline{M}_x^{\overline{m-im}}, \overline{N}_x^{\overline{m-re}} + \iota \overline{N}_x^{\overline{m-im}} \right)$ and $B'_x = \left(\overline{M}_x^{\overline{m-re}} + \iota \overline{M}_x^{\overline{m-im}}, \overline{N}_x^{\overline{m-re}} + \iota \overline{N}_x^{\overline{m-im}} \right)$

$\overline{N}_x^{\overbrace{m-im}})$ be two collections of Cq-ROFNs with $(x = 1, 2, \dots, m)$. If $B_x \leq B'_x$ for all x , then

$$Cq - ROFAAWA(B_1, B_2, \dots, B_m) \leq Cq - ROFAAWA(B'_1, B'_2, \dots, B'_m).$$

Definition 6. Let $B_x = (\overline{M}_x^{\overbrace{m}}, \overline{N}_x^{\overbrace{m}}) = \left(\overline{M}_x^{\overbrace{m-re}} + \iota \overline{M}_x^{\overbrace{m-im}}, \overline{N}_x^{\overbrace{m-re}} + \iota \overline{N}_x^{\overbrace{m-im}} \right)$ $(x = 1, 2, \dots, m)$ represent a collection of Cq-ROFNs. Accordingly, the Cq-ROFAAWG operator is expressed as:

$$Cq - ROFAAWG(B_1, B_2, \dots, B_m) = \prod_{x=1}^m (B_x)^{\bar{w}_x} \quad (3)$$

Where, $\bar{w} = (\bar{w}_1, \bar{w}_2, \bar{w}_3, \dots, \bar{w}_m)$ is the associated weight vector subject to conditions $0 \leq \bar{w}_x \leq 1$ and $\sum_{x=1}^m \bar{w}_x = 1$.

Theorem 5. Utilizing the proposed aggregation operator in Equation (3), it is ensured that the aggregated result retains the Cq-ROFN form. Furthermore,

$$Cq - ROFAAWG(B_1, B_2, \dots, B_m) = \left(e^{-\left\{ \sum_{x=1}^m \left(\left((-\ln(\overline{M}_x^{\overbrace{m-re}}))^{\bar{q} \kappa \frac{1}{\kappa}} \right) \right)^{\bar{w}_x} \right\}} + \iota e^{-\left\{ \sum_{x=1}^m \left(\left((-\ln(\overline{M}_x^{\overbrace{m-im}}))^{\bar{q} \kappa \frac{1}{\kappa}} \right) \right)^{\bar{w}_x} \right\}}, \sqrt[\bar{q}]{1 - e^{-\left\{ \sum_{x=1}^m \left(\left((-\ln(1 - \overline{N}_x^{\overbrace{m-re}}))^{\kappa \frac{1}{\kappa}} \right) \right)^{\bar{w}_x} \right\}}} + \iota \sqrt[\bar{q}]{1 - e^{-\left\{ \sum_{x=1}^m \left(\left((-\ln(1 - \overline{N}_x^{\overbrace{m-im}}))^{\kappa \frac{1}{\kappa}} \right) \right)^{\bar{w}_x} \right\}}} \right).$$

Proof. By using the mathematical induction rule.

(i) Let $m = 2$. Then

$$Cq - ROFAAWG(B_1, B_2) = \bar{w}_1 B_1 \otimes \bar{w}_2 B_2 = \left(\left(e^{-\left\{ \left((-\ln(\overline{M}_1^{\overbrace{m-re}}))^{\bar{q} \kappa \frac{1}{\kappa}} \right)^{\bar{w}_1} \right\}} + \iota e^{-\left\{ \left((-\ln(\overline{M}_1^{\overbrace{m-im}}))^{\bar{q} \kappa \frac{1}{\kappa}} \right)^{\bar{w}_1} \right\}}, \sqrt[\bar{q}]{1 - e^{-\left\{ \left((-\ln(1 - \overline{N}_1^{\overbrace{m-re}}))^{\kappa \frac{1}{\kappa}} \right)^{\bar{w}_1} \right\}}} + \iota \sqrt[\bar{q}]{1 - e^{-\left\{ \left((-\ln(1 - \overline{N}_1^{\overbrace{m-im}}))^{\kappa \frac{1}{\kappa}} \right)^{\bar{w}_1} \right\}}} \right) \otimes \left(e^{-\left\{ \left((-\ln(\overline{M}_2^{\overbrace{m-re}}))^{\bar{q} \kappa \frac{1}{\kappa}} \right)^{\bar{w}_2} \right\}} + \iota e^{-\left\{ \left((-\ln(\overline{M}_2^{\overbrace{m-im}}))^{\bar{q} \kappa \frac{1}{\kappa}} \right)^{\bar{w}_2} \right\}}, \sqrt[\bar{q}]{1 - e^{-\left\{ \left((-\ln(1 - \overline{N}_2^{\overbrace{m-re}}))^{\kappa \frac{1}{\kappa}} \right)^{\bar{w}_2} \right\}}} + \iota \sqrt[\bar{q}]{1 - e^{-\left\{ \left((-\ln(1 - \overline{N}_2^{\overbrace{m-im}}))^{\kappa \frac{1}{\kappa}} \right)^{\bar{w}_2} \right\}}} \right)$$

$$= \left(\frac{e^{-\left\{ \sum_{x=1}^2 \left(\overbrace{(-\ln(\overline{M}_x^m - re))^{\tilde{q} \kappa \frac{1}{\kappa}}} \right)} \right\}^{\tilde{w}_x}} + \iota e^{-\left\{ \sum_{x=1}^2 \left(\overbrace{(-\ln(\overline{M}_x^m - im))^{\tilde{q} \kappa \frac{1}{\kappa}}} \right)} \right\}^{\tilde{w}_x}}}{\sqrt[\tilde{q}]{1-e^{-\left\{ \sum_{x=1}^2 \left(\overbrace{(-\ln(1-\overline{N}_x^m - re))^{\kappa \frac{1}{\kappa}}} \right)} \right\}^{\tilde{w}_x}}} + \iota \sqrt[\tilde{q}]{1-e^{-\left\{ \sum_{x=1}^2 \left(\overbrace{(-\ln(1-\overline{N}_x^m - im))^{\kappa \frac{1}{\kappa}}} \right)} \right\}^{\tilde{w}_x}}}} \right)$$

Hence the result is true for $\mathfrak{m} = 2$.

(ii) Now suppose that the result is true for $\mathfrak{m} = g$

$$\begin{aligned} & Cq - ROFAAWG(\mathbf{B}_1, \mathbf{B}_2, \dots, \mathbf{B}_{\mathfrak{m}}) \\ &= \left(\frac{e^{-\left\{ \sum_{x=1}^g \left(\overbrace{(-\ln(\overline{M}_x^m - re))^{\tilde{q} \kappa \frac{1}{\kappa}}} \right)} \right\}^{\tilde{w}_x}} + \iota e^{-\left\{ \sum_{x=1}^g \left(\overbrace{(-\ln(\overline{M}_x^m - im))^{\tilde{q} \kappa \frac{1}{\kappa}}} \right)} \right\}^{\tilde{w}_x}}}{\sqrt[\tilde{q}]{1-e^{-\left\{ \sum_{x=1}^g \left(\overbrace{(-\ln(1-\overline{N}_x^m - re))^{\kappa \frac{1}{\kappa}}} \right)} \right\}^{\tilde{w}_x}}} + \iota \sqrt[\tilde{q}]{1-e^{-\left\{ \sum_{x=1}^g \left(\overbrace{(-\ln(1-\overline{N}_x^m - im))^{\kappa \frac{1}{\kappa}}} \right)} \right\}^{\tilde{w}_x}}}} \right) \end{aligned}$$

Now for $\mathfrak{m} = g + 1$

$$\begin{aligned} & Cq - ROFAAWG(\mathbf{B}_1, \mathbf{B}_2, \dots, \mathbf{B}_g, \mathbf{B}_{g+1}) = \prod_{x=1}^g (\tilde{w}_x \mathbf{B}_x) \otimes \tilde{w}_{g+1} \mathbf{B}_{g+1} \\ &= \left(\left(\frac{e^{-\left\{ \sum_{x=1}^g \left(\overbrace{\left(\overbrace{(-\ln(\overline{M}_x^m - re))^{\tilde{q} \kappa \frac{1}{\kappa}}} \right)^{\kappa \frac{1}{\kappa}}} \right)} \right\}^{\tilde{w}_x}} + \iota e^{-\left\{ \sum_{x=1}^g \left(\overbrace{\left(\overbrace{(-\ln(\overline{M}_x^m - im))^{\tilde{q} \kappa \frac{1}{\kappa}}} \right)^{\kappa \frac{1}{\kappa}}} \right)} \right\}^{\tilde{w}_x}}}{\sqrt[\tilde{q}]{1-e^{-\left\{ \sum_{x=1}^g \left(\overbrace{\left(\overbrace{(-\ln(1-\overline{N}_x^m - re))^{\kappa \frac{1}{\kappa}}} \right)^{\kappa \frac{1}{\kappa}}} \right)} \right\}^{\tilde{w}_x}}} + \iota \sqrt[\tilde{q}]{1-e^{-\left\{ \sum_{x=1}^g \left(\overbrace{\left(\overbrace{(-\ln(1-\overline{N}_x^m - im))^{\kappa \frac{1}{\kappa}}} \right)^{\kappa \frac{1}{\kappa}}} \right)} \right\}^{\tilde{w}_x}}} \right) \otimes \right. \\ & \quad \left(\frac{e^{-\left\{ \left(\overbrace{(-\ln(\overline{M}_{g+1}^m - re))^{\tilde{q} \kappa \frac{1}{\kappa}}} \right)^{\tilde{w}_{g+1}} \right\}} + \iota e^{-\left\{ \left(\overbrace{(-\ln(\overline{M}_{g+1}^m - im))^{\tilde{q} \kappa \frac{1}{\kappa}}} \right)^{\tilde{w}_{g+1}} \right\}}}{\sqrt[\tilde{q}]{1-e^{-\left\{ \left(\overbrace{(-\ln(1-\overline{N}_{g+1}^m - re))^{\kappa \frac{1}{\kappa}}} \right)^{\tilde{w}_{g+1}} \right\}}} + \iota \sqrt[\tilde{q}]{1-e^{-\left\{ \left(\overbrace{(-\ln(1-\overline{N}_{g+1}^m - im))^{\kappa \frac{1}{\kappa}}} \right)^{\tilde{w}_{g+1}} \right\}}} \right) \\ &= \left(\frac{e^{-\left\{ \sum_{x=1}^{g+1} \left(\overbrace{\left(\overbrace{(-\ln(\overline{M}_x^m - re))^{\tilde{q} \kappa \frac{1}{\kappa}}} \right)^{\kappa \frac{1}{\kappa}}} \right)} \right\}^{\tilde{w}_x}} + \iota e^{-\left\{ \sum_{x=1}^{g+1} \left(\overbrace{\left(\overbrace{(-\ln(\overline{M}_x^m - im))^{\tilde{q} \kappa \frac{1}{\kappa}}} \right)^{\kappa \frac{1}{\kappa}}} \right)} \right\}^{\tilde{w}_x}}}{\sqrt[\tilde{q}]{1-e^{-\left\{ \sum_{x=1}^{g+1} \left(\overbrace{\left(\overbrace{(-\ln(1-\overline{N}_x^m - re))^{\kappa \frac{1}{\kappa}}} \right)^{\kappa \frac{1}{\kappa}}} \right)} \right\}^{\tilde{w}_x}}} + \iota \sqrt[\tilde{q}]{1-e^{-\left\{ \sum_{x=1}^{g+1} \left(\overbrace{\left(\overbrace{(-\ln(1-\overline{N}_x^m - im))^{\kappa \frac{1}{\kappa}}} \right)^{\kappa \frac{1}{\kappa}}} \right)} \right\}^{\tilde{w}_x}}} \right) \end{aligned}$$

Hence, the result is true for all positive integers $\mathfrak{m}$. □

Theorem 6 (Idempotency Property). Let $B_x = (\overline{M}_x^m, \overline{N}_x^m) = \left(\overline{M}_x^m - re + \iota \overline{M}_x^m - im, \overline{N}_x^m - re + \iota \overline{N}_x^m - im \right) (x = 1, 2, \dots, \mathfrak{m})$ represent a

collection of Cq-ROFNs. If all B_m are identical, i.e., $B_m = B$, then

$$Cq - ROFAAWG(B_1, B_2, \dots, B_m) = B.$$

Theorem 7 (Boundedness Property). Let $B_x = (\overline{M}_x^m, \overline{N}_x^m) = \left(\overline{M}_x^{m-re} + \iota \overline{M}_x^{m-im}, \overline{N}_x^{m-re} + \iota \overline{N}_x^{m-im} \right)$ ($x = 1, 2, \dots, m$) represent a collection of Cq-ROFNs. If $B^- = \min(B_1, B_2, \dots, B_m)$ and $B^+ = \max(B_1, B_2, \dots, B_m)$, then

$$B^- \leq Cq - ROFAAWG(B_1, B_2, \dots, B_m) \leq B^+.$$

Theorem 8 (Monotonicity Property). Let $B_x = \left(\overline{M}_x^{m-re} + \iota \overline{M}_x^{m-im}, \overline{N}_x^{m-re} + \iota \overline{N}_x^{m-im} \right)$ and $B'_x = \left(\overline{M}_x^{m-re} + \iota \overline{M}_x^{m-im}, \overline{N}_x^{m-re} + \iota \overline{N}_x^{m-im} \right)$ be two collections of Cq-ROFNs with ($x = 1, 2, \dots, m$). If $B_x \leq B'_x$ for all x , then

$$Cq - ROFAAWG(B_1, B_2, \dots, B_m) \leq Cq - ROFAAWG(B'_1, B'_2, \dots, B'_m).$$

6. CRITIC-WASPAS approach

This section employs the proposed Aczel–Alsina aggregation operators to construct a Temporal-Aware CRITIC-WASPAS decision-making framework under the Cq-ROFN environment. Examine an MCDM problem that consists of $\wp$ alternatives $(\mathbb{P}_1, \mathbb{P}_2, \dots, \mathbb{P}_\wp)$, evaluated over x distinct attributes $(\mathbb{A}_1, \mathbb{A}_2, \dots, \mathbb{A}_f)$ across T temporal evaluation periods $(t_1, t_2, \dots, t_T)$. For each temporal period t_T a decision matrix $\mathbb{H}^{t_T} = [d_{ij}^{t_T}]$ is constructed. For illustrative purposes, five temporal decision matrices are considered in the study; however, the proposed framework applies to any number of temporal periods. A temporal weight vector is given as $\mathbb{W} = (\mathbb{W}_1, \mathbb{W}_2, \dots, \mathbb{W}_T)$, where $\mathbb{W}_c \in [0, 1]$ and $\sum_{c=1}^T \mathbb{W}_c = 1$. Since recent evaluations provide more representative information for future energy planning, higher temporal weights will be assigned to more recent periods. The proposed Aczel–Alsina aggregation operators are then applied to aggregate the temporal decision matrices into a collective decision matrix. Subsequently, the CRITIC method is applied to determine the weights of attributes. Where the weight of attributes is given by $\bar{\mathbb{w}} = (\bar{\mathbb{w}}_1, \bar{\mathbb{w}}_2, \dots, \bar{\mathbb{w}}_f)$, where $\bar{\mathbb{w}}_c \in [0, 1]$ and $\sum_{a=1}^f \bar{\mathbb{w}}_c = 1$.

The algorithm of CRITIC-WASPAS is shown in **Figure 4**.

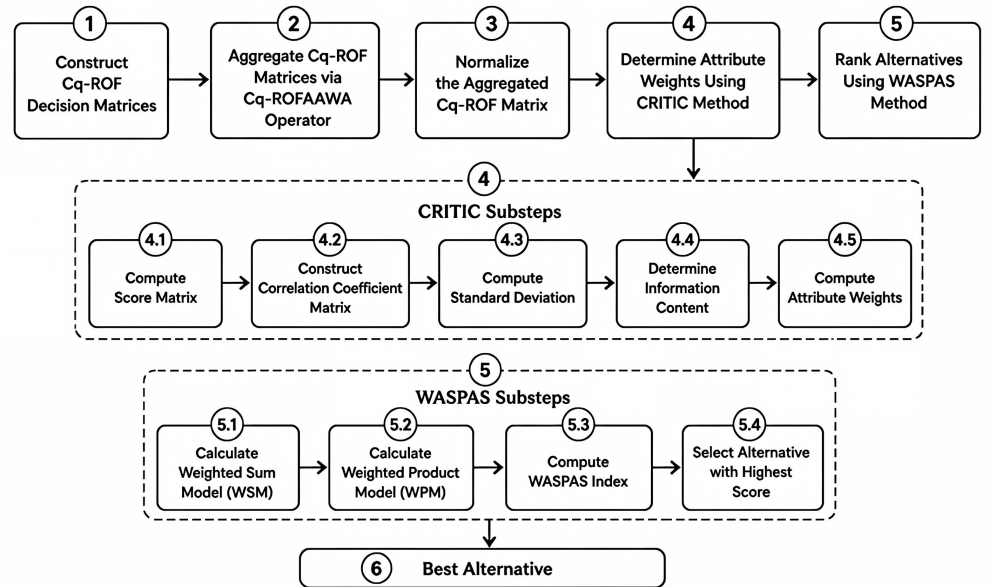


Figure 4. CRITIC-WASPAS algorithm flowchart.

The CRITIC-WASPAS procedure is carried out through the following sequential steps:

Step 1: Construct the Cq-ROF matrices for each time period.

$$\mathbb{H}_{cd}^t = \left(\begin{array}{ccc} \left(\overline{M}_{11}^{m-re} + \iota \overline{M}_{11}^{m-im} \right)^t, & \left(\overline{M}_{12}^{m-re} + \iota \overline{M}_{12}^{m-im} \right)^t, & \dots, \left(\overline{M}_{1b}^{m-re} + \iota \overline{M}_{1b}^{m-im} \right)^t, \\ \left(\overline{N}_{11}^{m-re} + \iota \overline{N}_{11}^{m-im} \right)^t, & \left(\overline{N}_{12}^{m-re} + \iota \overline{N}_{12}^{m-im} \right)^t, & \dots, \left(\overline{N}_{1b}^{m-re} + \iota \overline{N}_{1b}^{m-im} \right)^t, \\ \left(\overline{M}_{21}^{m-re} + \iota \overline{M}_{21}^{m-im} \right)^t, & \left(\overline{M}_{22}^{m-re} + \iota \overline{M}_{22}^{m-im} \right)^t, & \dots, \left(\overline{M}_{2b}^{m-re} + \iota \overline{M}_{2b}^{m-im} \right)^t, \\ \left(\overline{N}_{21}^{m-re} + \iota \overline{N}_{21}^{m-im} \right)^t, & \left(\overline{N}_{22}^{m-re} + \iota \overline{N}_{22}^{m-im} \right)^t, & \dots, \left(\overline{N}_{2b}^{m-re} + \iota \overline{N}_{2b}^{m-im} \right)^t, \\ \vdots & \vdots & \vdots \\ \left(\overline{M}_{a1}^{m-re} + \iota \overline{M}_{a1}^{m-im} \right)^t, & \left(\overline{M}_{a2}^{m-re} + \iota \overline{M}_{a2}^{m-im} \right)^t, & \dots, \left(\overline{M}_{ab}^{m-re} + \iota \overline{M}_{ab}^{m-im} \right)^t, \\ \left(\overline{N}_{a1}^{m-re} + \iota \overline{N}_{a1}^{m-im} \right)^t, & \left(\overline{N}_{a2}^{m-re} + \iota \overline{N}_{a2}^{m-im} \right)^t, & \dots, \left(\overline{N}_{ab}^{m-re} + \iota \overline{N}_{ab}^{m-im} \right)^t \end{array} \right)$$

Step 2: Now aggregate the Cq-ROF matrices with the help of the Cq-ROFAAWA operator.

$$\mathbb{H}_{cd} = \left(\begin{array}{ccc} \left(\overline{M}_{11}^{m-re} + \iota \overline{M}_{11}^{m-im}, \right. & \left. \overline{N}_{11}^{m-re} + \iota \overline{N}_{11}^{m-im} \right) & \left(\overline{M}_{12}^{m-re} + \iota \overline{M}_{12}^{m-im}, \right. & \left. \overline{N}_{12}^{m-re} + \iota \overline{N}_{12}^{m-im} \right) & \dots & \left(\overline{M}_{1b}^{m-re} + \iota \overline{M}_{1b}^{m-im}, \right. & \left. \overline{N}_{1b}^{m-re} + \iota \overline{N}_{1b}^{m-im} \right) \\ \left(\overline{M}_{21}^{m-re} + \iota \overline{M}_{21}^{m-im}, \right. & \left. \overline{N}_{21}^{m-re} + \iota \overline{N}_{21}^{m-im} \right) & \left(\overline{M}_{22}^{m-re} + \iota \overline{M}_{22}^{m-im}, \right. & \left. \overline{N}_{22}^{m-re} + \iota \overline{N}_{22}^{m-im} \right) & \dots & \left(\overline{M}_{2b}^{m-re} + \iota \overline{M}_{2b}^{m-im}, \right. & \left. \overline{N}_{2b}^{m-re} + \iota \overline{N}_{2b}^{m-im} \right) \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \left(\overline{M}_{a1}^{m-re} + \iota \overline{M}_{a1}^{m-im}, \right. & \left. \overline{N}_{a1}^{m-re} + \iota \overline{N}_{a1}^{m-im} \right) & \left(\overline{M}_{a2}^{m-re} + \iota \overline{M}_{a2}^{m-im}, \right. & \left. \overline{N}_{a2}^{m-re} + \iota \overline{N}_{a2}^{m-im} \right) & \dots & \left(\overline{M}_{ab}^{m-re} + \iota \overline{M}_{ab}^{m-im}, \right. & \left. \overline{N}_{ab}^{m-re} + \iota \overline{N}_{ab}^{m-im} \right) \end{array} \right)$$

$$\mathbb{H}_{cd} = \begin{pmatrix} \xi_{11} & \xi_{12} & \dots & \xi_{1b} \\ \xi_{21} & \xi_{22} & \dots & \xi_{2b} \\ \vdots & \vdots & \vdots & \vdots \\ \xi_{a1} & \xi_{a2} & \dots & \xi_{ab} \end{pmatrix}$$

Step 3: Normalization of the Cq-ROF matrix.

(i) For benefit-type attributes

$$\mathbb{H}'_{cd} = \left\{ \overline{M}_{cd}^{\overline{m-re}} + \iota \overline{M}_{cd}^{\overline{m-im}}, \overline{N}_{cd}^{\overline{m-re}} + \iota \overline{N}_{cd}^{\overline{m-im}} \right\}$$

(ii) For cost-type criteria, the complement-based normalization method is adopted to convert cost attributes into benefit attributes. The transformation is applied to both real and imaginary components of membership and non-membership degrees. After normalization, the obtained Cq-ROF values are checked to ensure that they satisfy the admissibility conditions of Cq-ROFNs, thereby preserving the validity of the normalized decision matrix within the proposed framework.

$$\mathbb{H}'_{cd} = \left\{ (1 - \overline{M}_{cd}^{\overline{m-re}}) + \iota (1 - \overline{M}_{cd}^{\overline{m-im}}), (1 - \overline{N}_{cd}^{\overline{m-re}}) + \iota (1 - \overline{N}_{cd}^{\overline{m-im}}) \right\}$$

Step 4: Determination of attribute weights using the CRITIC method.

Step 4.1: Compute the associated score matrix of the normalized Cq-ROF matrix.

$$E_{cd} = \begin{bmatrix} \epsilon_{11} & \epsilon_{12} & \cdots & \epsilon_{1b} \\ \epsilon_{21} & \epsilon_{22} & \cdots & \epsilon_{2b} \\ \vdots & \vdots & \ddots & \vdots \\ \epsilon_{a1} & \epsilon_{a2} & \cdots & \epsilon_{ab} \end{bmatrix}$$

Step 4.2: Construct the correlation coefficient matrix.

$$\epsilon_{gh} = \frac{\sum_{f=1}^a (\epsilon_{fg} - \overline{\epsilon}_g) (\epsilon_{fh} - \overline{\epsilon}_h)}{\sqrt{\sum_{f=1}^a (\epsilon_{fg} - \overline{\epsilon}_g)^2 \sum_{f=1}^a (\epsilon_{fh} - \overline{\epsilon}_h)^2}}$$

Step 4.3: Compute the standard deviation of each attribute.

$$S_g = \sqrt{\frac{\sum_{f=1}^a (\epsilon_{fg} - \overline{\epsilon}_g)^2}{a}}$$

Step 4.4: Next, the amount of information corresponding to each attribute is determined.

$$\tilde{V}_g = S_g \sum_{h=1}^b (1 - \epsilon_{gh}), \quad g = 1, 2, \dots, a$$

Step 4.5: Compute attribute weights.

$$\bar{w}_g = \tilde{V}_g / \sum_{g=1}^a \tilde{V}_g$$

Step 5: Now, to rank the alternatives, we use the WASPAS technique.

Step 5.1: Calculation of the weighted sum model (WSM) with the help of

$$\bar{Q}_c^1 = \sum_{d=1}^n \bar{w}_d \mathbb{H}_{cd}$$

Step 5.2: Calculation of the weighted product model (WPS) with the help of

$$\bar{Q}_c^2 = \prod_{d=1}^n (\mathbb{H}_{cd})^{\bar{w}_d}$$

Step 5.3: Calculation of WASPAS index with the help of the convex formula

$$\bar{Q}_c = \lambda \bar{Q}_c^1 + (1 - \lambda) \bar{Q}_c^2$$

where $0 \leq \lambda \leq 1$.

Step 5.4: The best alternative is one that has the highest score value.

6.1. Case study

The case study presented in this work is illustrative and is intended to demonstrate the applicability of the proposed mathematical framework. Five hypothetical temporal decision matrices corresponding to consecutive evaluation periods are considered under the selected evaluation criteria. A temporal weighting strategy is employed to assign greater importance to recent evaluation periods before aggregation. Since the primary objective of this study is methodological development, hypothetical evaluations are used solely for illustration, and the proposed framework can be readily extended to real-world temporal datasets.

Accurate and sustainable energy planning is critical for ensuring operational efficiency, cost-effectiveness, and environmental resilience in modern energy systems. Conventional planning approaches, such as static modeling, expert surveys, and deterministic optimization, often struggle with complex temporal dynamics, uncertain future demand, and conflicting stakeholder priorities, leading to suboptimal decisions, elevated costs, and reduced system robustness.

Need for Evaluation: Multidimensional uncertainty, hesitation, and time variation in energy planning are represented by new schemes founded on Cq-ROFSs. They are not practical because of the differences in their competing aspects, including economic viability, environmental sustainability, reliability, adaptability, and acceptability by stakeholders, and are influenced by unavailable information and prejudice by experts. This points to the serious necessity of a powerful, structured, and uncertain MCDM paradigm to the level of informing resilient, effective, and sustainable energy strategy choice.

Efficiency of the Proposed Framework: The Temporal-Aware Cq-ROF-CRITIC-WASPAS framework solves these issues by combining sophisticated uncertainty modeling, objective criterion weighting, and effective ranking of alternatives. CRITIC guarantees that high-impact, low-redundancy criteria are given priority, whereas WASPAS amalgamates additive and multiplicative scores to make transparent, quantitative, and flexible decisions. Together, this framework enables the selection of energy strategies that optimize economic efficiency, environmental sustainability, and long-term resilience, providing policymakers with a powerful, data-driven, and future-ready tool for sustainable energy planning.

The various options studied were chosen to encompass a wide variety of new and advanced energy technologies that are likely to be important in future low-

carbon energy systems. The chosen options reflect clean energy generation technologies, carbon mitigation measures, advanced energy storage technologies, smart energy management solutions, and cross-border energy infrastructure; all are integral to the assessment of future energy planning options in the context of uncertainty. While wind energy has a significant future in the renewable energy sector, for the sake of the present study, a representative group of advanced and emerging wind technologies was selected in order to showcase the applicability of the proposed temporal-aware Cq-ROF-AA-CRITIC-WASPAS framework. The proposed methodology is sufficiently general to be easily expanded to accommodate wind energy or any other energy technology in future real-world applications, without any changes to the framework. The chosen alternatives for future energy planning are discussed in **Table 2**.

Table 2. Alternatives for future energy planning.

Symbol	Alternative	Description
P ₁	Centralized Green Hydrogen Production & Export Hubs	Large-scale renewable-powered electrolysis systems integrated with hydrogen storage, pipelines, and export terminals. These centers enable the deep decarbonization of the industry, transport, and power. They are expensive in terms of capital investment as well as long-term planning of the infrastructure, but bear significant strategic as well as geopolitical value.
P ₂	Generation-IV Small Modular Reactors (SMRs)	Intensive modular nuclear reactors are designed to increase safety and versatility, and reduce the time to be built compared to traditional ones. SMRs are reliable base-load sources of low operational emissions. Nonetheless, the uncertainties include regulatory approval, capital cost, and acceptance by the population.
P ₃	Concentrated Solar Power (CSP) with Molten Salt Storage	Mirror-based solar thermal systems that store energy as electricity in molten salts in the form of heat, which is used to produce dispatchable electricity. CSP provides renewable baseload capability but is geographically constrained to high solar irradiance regions. It competes with battery storage in cost and scalability.
P ₄	Transnational High-Voltage Super-Grid Interconnections	Cross-border HVDC transmission infrastructure enabling regional energy exchange and renewable balancing. Super-grids enhance grid security and stability but increase geopolitical interdependence. These require longer planning periods and multifaceted coordination of regulatory procedures.
P ₅	Biomass-to-Energy with Carbon Capture and Storage (BECCS)	There were carbon capture systems installed in the bioenergy plants, and they would be in a position to emit negative emissions. BECCS encourages a carbon-zero approach and a net-zero approach. However, there are concerns regarding the use of land, the viability of supplying biomass, and storage.
P ₆	Deep Geothermal Energy Systems (Power & District Heating)	Enhanced geothermal systems extract heat from deep underground reservoirs for a continuous electricity and heating supply. These systems provide stable baseload energy with minimal emissions. Their feasibility depends heavily on geological conditions and drilling technology advancements.
P ₇	Retrofitted Natural Gas Plants with Advanced Carbon Capture (CCS)	High-efficiency carbon capture technologies were introduced in the gas-fired plants in order to reduce emissions. The alternative is used as an intermediate measure in decarbonization. Its sustainability in the long term is pegged on the pricing of carbon, storage facilities, and regulations.
P ₈	Utility-Scale Electrochemical Energy Storage Systems (Li-ion & Flow Batteries)	Large-scale battery installations supporting renewable integration, grid stability, and peak shaving. The technological changes are rapid, which are cutting down on costs and increasing output. Still, the material supply risk and environmental problems of the lifecycle remain critical considerations as well.
P ₉	Digitally Integrated Virtual Power Plants (VPP) & Demand-Side Flexibility	Aggregation of distributed energy resources, storage, and demand response into a coordinated virtual system with the help of AI. The VPPs enhance flexibility and reduce the infrastructural requirements. They work well with the digital infrastructure, regulatory assurance, and cybersecurity resiliency.
P ₁₀	Marine Renewable Energy Systems (Tidal & Wave)	The tidal currents and the movement of waves are transformed into electricity using ocean-based technologies. These systems are a predictable, renewable source of generation with small land utilization. Nonetheless, there are technological immaturity, expensive nature, and environmental impact measures, which are issues.

Considering that the goal of the research is to show the applicability of the proposed temporal-aware Cq-ROF-AA-CRITIC-WASPAS framework in a hypothetical case study, the evaluation criteria were selected in a manner that reflects the most common criteria used in future energy planning. The key factors for

evaluating long-term energy strategies that were selected for this study are economic viability, environmental sustainability, technological preparedness, energy security, and policy flexibility. The above factors are well known and addressed in past energy planning studies [1–5]. These are also criteria that become increasingly relevant for future energy decision making due to recent research on sustainable energy systems and long-term planning under uncertainty [6–9]. The case study itself is fictional, but the criteria chosen are realistic and represent the key technical, economic, environmental, and policy issues that are likely to arise in real-world energy planning. The attributes are discussed in **Table 3**.

Table 3. Attributes for future energy planning.

Symbol	Attribute	Description
A_1	Temporal Dispatchability & Reliability	Evaluates the ability of an energy source to consistently meet demand over time, accounting for variability, peak loads, and system stability.
A_2	Lifecycle Economic Viability	Determines the total cost-effectiveness of an energy system, including initial capital expenditure, operating cost, and levelized cost of electricity over the lifespan of the system.
A_3	Environmental Impact & Carbon Abatement Potential	Assesses the ecological footprint of the source of energy, including reduction of emissions, potential of carbon mitigation, and sustainability objectives.
A_4	Technological Maturity & Scalability	Analyzes technology preparedness and flexibility, such as demonstrated functionality, scalability, and innovativeness.
A_5	Socio-Political & Regulatory Resilience	Takes into account the stability of policies, their social acceptance, compliance with regulations, and the capacity of the energy system to endure political or societal shifts.

6.2. Numerical example

To illustrate the proposed framework, five hypothetical temporal decision matrices representing different time periods are constructed to evaluate ten future energy planning alternatives across five attributes. Temporal weights (0.13, 0.18, 0.21, 0.23, 0.25) are assigned to each matrix, with greater importance given to recent assessments. After temporal aggregation, the CRITIC method is used to determine objective attribute weights, and the WASPAS approach is applied to compute appraisal scores and rank the alternatives, demonstrating the applicability of the proposed temporal-aware decision framework. Where $q = 3$.

Step 1: The initial temporal decision matrices for the five evaluation periods are shown in **Tables 4–8**.

Table 4. Temporal matrix 1.

	A_1	A_2	A_3	A_4	A_5
P_1	$\begin{pmatrix} 0.620 + i0.351, \\ 0.282 + i0.741 \end{pmatrix}$	$\begin{pmatrix} 0.561 + i0.720, \\ 0.442 + i0.392 \end{pmatrix}$	$\begin{pmatrix} 0.051 + i0.461, \\ 0.711 + i0.580 \end{pmatrix}$	$\begin{pmatrix} 0.282 + i0.460, \\ 0.821 + i0.542 \end{pmatrix}$	$\begin{pmatrix} 0.362 + i0.481, \\ 0.580 + i0.531 \end{pmatrix}$
P_2	$\begin{pmatrix} 0.381 + i0.580, \\ 0.615 + i0.351 \end{pmatrix}$	$\begin{pmatrix} 0.271 + i0.130, \\ 0.672 + i0.721 \end{pmatrix}$	$\begin{pmatrix} 0.370 + i0.821, \\ 0.631 + i0.281 \end{pmatrix}$	$\begin{pmatrix} 0.562 + i0.531, \\ 0.490 + i0.480 \end{pmatrix}$	$\begin{pmatrix} 0.180 + i0.691, \\ 0.760 + i0.372 \end{pmatrix}$
P_3	$\begin{pmatrix} 0.251 + i0.722, \\ 0.740 + i0.251 \end{pmatrix}$	$\begin{pmatrix} 0.340 + i0.551, \\ 0.812 + i0.431 \end{pmatrix}$	$\begin{pmatrix} 0.861 + i0.343, \\ 0.420 + i0.831 \end{pmatrix}$	$\begin{pmatrix} 0.470 + i0.711, \\ 0.530 + i0.391 \end{pmatrix}$	$\begin{pmatrix} 0.681 + i0.380, \\ 0.391 + i0.761 \end{pmatrix}$
P_4	$\begin{pmatrix} 0.712 + i0.190, \\ 0.291 + i0.815 \end{pmatrix}$	$\begin{pmatrix} 0.480 + i0.471, \\ 0.422 + i0.591 \end{pmatrix}$	$\begin{pmatrix} 0.140 + i0.521, \\ 0.832 + i0.380 \end{pmatrix}$	$\begin{pmatrix} 0.931 + i0.172, \\ 0.191 + i0.760 \end{pmatrix}$	$\begin{pmatrix} 0.722 + i0.171, \\ 0.180 + i0.671 \end{pmatrix}$
P_5	$\begin{pmatrix} 0.381 + i0.470, \\ 0.631 + i0.492 \end{pmatrix}$	$\begin{pmatrix} 0.831 + i0.312, \\ 0.111 + i0.750 \end{pmatrix}$	$\begin{pmatrix} 0.530 + i0.721, \\ 0.470 + i0.411 \end{pmatrix}$	$\begin{pmatrix} 0.251 + i0.372, \\ 0.830 + i0.761 \end{pmatrix}$	$\begin{pmatrix} 0.491 + i0.582, \\ 0.531 + i0.382 \end{pmatrix}$
P_6	$\begin{pmatrix} 0.190 + i0.581, \\ 0.762 + i0.342 \end{pmatrix}$	$\begin{pmatrix} 0.750 + i0.921, \\ 0.252 + i0.281 \end{pmatrix}$	$\begin{pmatrix} 0.460 + i0.681, \\ 0.591 + i0.370 \end{pmatrix}$	$\begin{pmatrix} 0.371 + i0.672, \\ 0.562 + i0.381 \end{pmatrix}$	$\begin{pmatrix} 0.050 + i0.781, \\ 0.741 + i0.272 \end{pmatrix}$

Table 4. *Cont.*

	A_1	A_2	A_3	A_4	A_5
P_7	$\begin{pmatrix} 0.371 + i0.732, \\ 0.583 + i0.290 \end{pmatrix}$	$\begin{pmatrix} 0.370 + i0.741, \\ 0.732 + i0.352 \end{pmatrix}$	$\begin{pmatrix} 0.751 + i0.490, \\ 0.370 + i0.141 \end{pmatrix}$	$\begin{pmatrix} 0.180 + i0.531, \\ 0.730 + i0.462 \end{pmatrix}$	$\begin{pmatrix} 0.561 + i0.392, \\ 0.381 + i0.620 \end{pmatrix}$
P_8	$\begin{pmatrix} 0.821 + i0.632, \\ 0.140 + i0.571 \end{pmatrix}$	$\begin{pmatrix} 0.120 + i0.291, \\ 0.830 + i0.711 \end{pmatrix}$	$\begin{pmatrix} 0.620 + i0.341, \\ 0.281 + i0.571 \end{pmatrix}$	$\begin{pmatrix} 0.251 + i0.282, \\ 0.741 + i0.680 \end{pmatrix}$	$\begin{pmatrix} 0.711 + i0.470, \\ 0.282 + i0.411 \end{pmatrix}$
P_9	$\begin{pmatrix} 0.471 + i0.550, \\ 0.532 + i0.631 \end{pmatrix}$	$\begin{pmatrix} 0.661 + i0.582, \\ 0.431 + i0.220 \end{pmatrix}$	$\begin{pmatrix} 0.280 + i0.371, \\ 0.731 + i0.432 \end{pmatrix}$	$\begin{pmatrix} 0.370 + i0.491, \\ 0.682 + i0.530 \end{pmatrix}$	$\begin{pmatrix} 0.460 + i0.371, \\ 0.521 + i0.580 \end{pmatrix}$
P_{10}	$\begin{pmatrix} 0.580 + i0.271, \\ 0.461 + i0.470 \end{pmatrix}$	$\begin{pmatrix} 0.230 + i0.341, \\ 0.682 + i0.661 \end{pmatrix}$	$\begin{pmatrix} 0.352 + i0.420, \\ 0.491 + i0.481 \end{pmatrix}$	$\begin{pmatrix} 0.091 + i0.352, \\ 0.760 + i0.751 \end{pmatrix}$	$\begin{pmatrix} 0.350 + i0.140, \\ 0.731 + i0.861 \end{pmatrix}$

Table 5. Temporal matrix 2.

	A_1	A_2	A_3	A_4	A_5
P_1	$\begin{pmatrix} 0.470 + i0.171, \\ 0.551 + i0.830 \end{pmatrix}$	$\begin{pmatrix} 0.090 + i0.421, \\ 0.820 + i0.591 \end{pmatrix}$	$\begin{pmatrix} 0.870 + i0.461, \\ 0.331 + i0.510 \end{pmatrix}$	$\begin{pmatrix} 0.221 + i0.471, \\ 0.490 + i0.580 \end{pmatrix}$	$\begin{pmatrix} 0.109 + i0.690, \\ 0.830 + i0.379 \end{pmatrix}$
P_2	$\begin{pmatrix} 0.390 + i0.581, \\ 0.632 + i0.621 \end{pmatrix}$	$\begin{pmatrix} 0.531 + i0.590, \\ 0.411 + i0.470 \end{pmatrix}$	$\begin{pmatrix} 0.261 + i0.681, \\ 0.760 + i0.480 \end{pmatrix}$	$\begin{pmatrix} 0.481 + i0.359, \\ 0.530 + i0.810 \end{pmatrix}$	$\begin{pmatrix} 0.370 + i0.282, \\ 0.689 + i0.749 \end{pmatrix}$
P_3	$\begin{pmatrix} 0.161 + i0.280, \\ 0.760 + i0.712 \end{pmatrix}$	$\begin{pmatrix} 0.720 + i0.381, \\ 0.352 + i0.682 \end{pmatrix}$	$\begin{pmatrix} 0.341 + i0.070, \\ 0.821 + i0.372 \end{pmatrix}$	$\begin{pmatrix} 0.331 + i0.550, \\ 0.771 + i0.620 \end{pmatrix}$	$\begin{pmatrix} 0.580 + i0.061, \\ 0.460 + i0.671 \end{pmatrix}$
P_4	$\begin{pmatrix} 0.731 + i0.612, \\ 0.280 + i0.531 \end{pmatrix}$	$\begin{pmatrix} 0.312 + i0.520, \\ 0.630 + i0.491 \end{pmatrix}$	$\begin{pmatrix} 0.490 + i0.171, \\ 0.581 + i0.750 \end{pmatrix}$	$\begin{pmatrix} 0.049 + i0.762, \\ 0.850 + i0.410 \end{pmatrix}$	$\begin{pmatrix} 0.289 + i0.811, \\ 0.760 + i0.270 \end{pmatrix}$
P_5	$\begin{pmatrix} 0.580 + i0.370, \\ 0.471 + i0.812 \end{pmatrix}$	$\begin{pmatrix} 0.681 + i0.472, \\ 0.482 + i0.532 \end{pmatrix}$	$\begin{pmatrix} 0.610 + i0.522, \\ 0.472 + i0.510 \end{pmatrix}$	$\begin{pmatrix} 0.680 + i0.350, \\ 0.361 + i0.730 \end{pmatrix}$	$\begin{pmatrix} 0.730 + i0.190, \\ 0.379 + i0.722 \end{pmatrix}$
P_6	$\begin{pmatrix} 0.372 + i0.171, \\ 0.721 + i0.560 \end{pmatrix}$	$\begin{pmatrix} 0.410 + i0.321, \\ 0.720 + i0.772 \end{pmatrix}$	$\begin{pmatrix} 0.180 + i0.771, \\ 0.831 + i0.330 \end{pmatrix}$	$\begin{pmatrix} 0.431 + i0.741, \\ 0.619 + i0.352 \end{pmatrix}$	$\begin{pmatrix} 0.919 + i0.760, \\ 0.360 + i0.321 \end{pmatrix}$
P_7	$\begin{pmatrix} 0.250 + i0.421, \\ 0.691 + i0.750 \end{pmatrix}$	$\begin{pmatrix} 0.250 + i0.750, \\ 0.831 + i0.422 \end{pmatrix}$	$\begin{pmatrix} 0.530 + i0.361, \\ 0.350 + i0.631 \end{pmatrix}$	$\begin{pmatrix} 0.581 + i0.561, \\ 0.470 + i0.469 \end{pmatrix}$	$\begin{pmatrix} 0.539 + i0.510, \\ 0.140 + i0.489 \end{pmatrix}$
P_8	$\begin{pmatrix} 0.630 + i0.761, \\ 0.381 + i0.390 \end{pmatrix}$	$\begin{pmatrix} 0.330 + i0.491, \\ 0.612 + i0.612 \end{pmatrix}$	$\begin{pmatrix} 0.040 + i0.421, \\ 0.741 + i0.560 \end{pmatrix}$	$\begin{pmatrix} 0.730 + i0.131, \\ 0.341 + i0.850 \end{pmatrix}$	$\begin{pmatrix} 0.351 + i0.381, \\ 0.622 + i0.681 \end{pmatrix}$
P_9	$\begin{pmatrix} 0.270 + i0.371, \\ 0.751 + i0.622 \end{pmatrix}$	$\begin{pmatrix} 0.791 + i0.570, \\ 0.350 + i0.581 \end{pmatrix}$	$\begin{pmatrix} 0.370 + i0.821, \\ 0.351 + i0.252 \end{pmatrix}$	$\begin{pmatrix} 0.841 + i0.711, \\ 0.250 + i0.410 \end{pmatrix}$	$\begin{pmatrix} 0.481 + i0.470, \\ 0.551 + i0.582 \end{pmatrix}$
P_{10}	$\begin{pmatrix} 0.371 + i0.550, \\ 0.662 + i0.490 \end{pmatrix}$	$\begin{pmatrix} 0.450 + i0.640, \\ 0.591 + i0.251 \end{pmatrix}$	$\begin{pmatrix} 0.720 + i0.621, \\ 0.471 + i0.380 \end{pmatrix}$	$\begin{pmatrix} 0.681 + i0.282, \\ 0.430 + i0.760 \end{pmatrix}$	$\begin{pmatrix} 0.160 + i0.251, \\ 0.731 + i0.820 \end{pmatrix}$

Table 6. Temporal matrix 3.

	A_1	A_2	A_3	A_4	A_5
P_1	$\begin{pmatrix} 0.370 + i0.851, \\ 0.721 + i0.340 \end{pmatrix}$	$\begin{pmatrix} 0.550 + i0.491, \\ 0.582 + i0.411 \end{pmatrix}$	$\begin{pmatrix} 0.169 + i0.749, \\ 0.760 + i0.439 \end{pmatrix}$	$\begin{pmatrix} 0.409 + i0.549, \\ 0.509 + i0.360 \end{pmatrix}$	$\begin{pmatrix} 0.210 + i0.580, \\ 0.769 + i0.272 \end{pmatrix}$
P_2	$\begin{pmatrix} 0.180 + i0.442, \\ 0.881 + i0.580 \end{pmatrix}$	$\begin{pmatrix} 0.630 + i0.611, \\ 0.471 + i0.380 \end{pmatrix}$	$\begin{pmatrix} 0.761 + i0.420, \\ 0.341 + i0.472 \end{pmatrix}$	$\begin{pmatrix} 0.239 + i0.738, \\ 0.610 + i0.239 \end{pmatrix}$	$\begin{pmatrix} 0.350 + i0.489, \\ 0.691 + i0.322 \end{pmatrix}$
P_3	$\begin{pmatrix} 0.870 + i0.391, \\ 0.362 + i0.811 \end{pmatrix}$	$\begin{pmatrix} 0.759 + i0.179, \\ 0.349 + i0.792 \end{pmatrix}$	$\begin{pmatrix} 0.430 + i0.559, \\ 0.710 + i0.322 \end{pmatrix}$	$\begin{pmatrix} 0.789 + i0.391, \\ 0.349 + i0.789 \end{pmatrix}$	$\begin{pmatrix} 0.681 + i0.322, \\ 0.439 + i0.641 \end{pmatrix}$
P_4	$\begin{pmatrix} 0.381 + i0.650, \\ 0.450 + i0.471 \end{pmatrix}$	$\begin{pmatrix} 0.279 + i0.529, \\ 0.680 + i0.579 \end{pmatrix}$	$\begin{pmatrix} 0.379 + i0.369, \\ 0.418 + i0.619 \end{pmatrix}$	$\begin{pmatrix} 0.619 + i0.680, \\ 0.471 + i0.360 \end{pmatrix}$	$\begin{pmatrix} 0.549 + i0.470, \\ 0.380 + i0.581 \end{pmatrix}$
P_5	$\begin{pmatrix} 0.491 + i0.710, \\ 0.580 + i0.281 \end{pmatrix}$	$\begin{pmatrix} 0.471 + i0.721, \\ 0.450 + i0.452 \end{pmatrix}$	$\begin{pmatrix} 0.091 + i0.520, \\ 0.821 + i0.440 \end{pmatrix}$	$\begin{pmatrix} 0.439 + i0.469, \\ 0.529 + i0.550 \end{pmatrix}$	$\begin{pmatrix} 0.140 + i0.522, \\ 0.849 + i0.490 \end{pmatrix}$
P_6	$\begin{pmatrix} 0.770 + i0.381, \\ 0.350 + i0.682 \end{pmatrix}$	$\begin{pmatrix} 0.320 + i0.691, \\ 0.732 + i0.321 \end{pmatrix}$	$\begin{pmatrix} 0.571 + i0.680, \\ 0.511 + i0.341 \end{pmatrix}$	$\begin{pmatrix} 0.389 + i0.742, \\ 0.412 + i0.409 \end{pmatrix}$	$\begin{pmatrix} 0.459 + i0.333, \\ 0.671 + i0.830 \end{pmatrix}$
P_7	$\begin{pmatrix} 0.581 + i0.570, \\ 0.531 + i0.481 \end{pmatrix}$	$\begin{pmatrix} 0.750 + i0.381, \\ 0.421 + i0.750 \end{pmatrix}$	$\begin{pmatrix} 0.280 + i0.821, \\ 0.691 + i0.290 \end{pmatrix}$	$\begin{pmatrix} 0.113 + i0.550, \\ 0.921 + i0.480 \end{pmatrix}$	$\begin{pmatrix} 0.781 + i0.282, \\ 0.349 + i0.739 \end{pmatrix}$
P_8	$\begin{pmatrix} 0.690 + i0.482, \\ 0.451 + i0.550 \end{pmatrix}$	$\begin{pmatrix} 0.491 + i0.750, \\ 0.580 + i0.251 \end{pmatrix}$	$\begin{pmatrix} 0.371 + i0.171, \\ 0.510 + i0.810 \end{pmatrix}$	$\begin{pmatrix} 0.879 + i0.391, \\ 0.279 + i0.609 \end{pmatrix}$	$\begin{pmatrix} 0.081 + i0.642, \\ 0.761 + i0.351 \end{pmatrix}$

Table 6. *Cont.*

	A_1	A_2	A_3	A_4	A_5
P_9	$\begin{pmatrix} 0.471 + i0.631, \\ 0.582 + i0.360 \end{pmatrix}$	$\begin{pmatrix} 0.571 + i0.660, \\ 0.621 + i0.470 \end{pmatrix}$	$\begin{pmatrix} 0.570 + i0.060, \\ 0.421 + i0.791 \end{pmatrix}$	$\begin{pmatrix} 0.349 + i0.650, \\ 0.661 + i0.380 \end{pmatrix}$	$\begin{pmatrix} 0.831 + i0.352, \\ 0.282 + i0.621 \end{pmatrix}$
P_{10}	$\begin{pmatrix} 0.529 + i0.179, \\ 0.639 + i0.789 \end{pmatrix}$	$\begin{pmatrix} 0.640 + i0.341, \\ 0.270 + i0.680 \end{pmatrix}$	$\begin{pmatrix} 0.471 + i0.740, \\ 0.560 + i0.380 \end{pmatrix}$	$\begin{pmatrix} 0.210 + i0.439, \\ 0.739 + i0.559 \end{pmatrix}$	$\begin{pmatrix} 0.271 + i0.582, \\ 0.779 + i0.412 \end{pmatrix}$

Table 7. Temporal matrix 4.

	A_1	A_2	A_3	A_4	A_5
P_1	$\begin{pmatrix} 0.490 + i0.581, \\ 0.561 + i0.430 \end{pmatrix}$	$\begin{pmatrix} 0.349 + i0.289, \\ 0.681 + i0.589 \end{pmatrix}$	$\begin{pmatrix} 0.582 + i0.629, \\ 0.409 + i0.579 \end{pmatrix}$	$\begin{pmatrix} 0.749 + i0.339, \\ 0.350 + i0.742 \end{pmatrix}$	$\begin{pmatrix} 0.649 + i0.358, \\ 0.389 + i0.519 \end{pmatrix}$
P_2	$\begin{pmatrix} 0.251 + i0.340, \\ 0.611 + i0.611 \end{pmatrix}$	$\begin{pmatrix} 0.572 + i0.509, \\ 0.549 + i0.289 \end{pmatrix}$	$\begin{pmatrix} 0.189 + i0.279, \\ 0.772 + i0.738 \end{pmatrix}$	$\begin{pmatrix} 0.319 + i0.669, \\ 0.688 + i0.349 \end{pmatrix}$	$\begin{pmatrix} 0.349 + i0.049, \\ 0.738 + i0.748 \end{pmatrix}$
P_3	$\begin{pmatrix} 0.790 + i0.241, \\ 0.380 + i0.711 \end{pmatrix}$	$\begin{pmatrix} 0.212 + i0.819, \\ 0.738 + i0.178 \end{pmatrix}$	$\begin{pmatrix} 0.369 + i0.409, \\ 0.593 + i0.619 \end{pmatrix}$	$\begin{pmatrix} 0.179 + i0.549, \\ 0.748 + i0.583 \end{pmatrix}$	$\begin{pmatrix} 0.509 + i0.169, \\ 0.439 + i0.648 \end{pmatrix}$
P_4	$\begin{pmatrix} 0.631 + i0.490, \\ 0.462 + i0.411 \end{pmatrix}$	$\begin{pmatrix} 0.488 + i0.649, \\ 0.559 + i0.409 \end{pmatrix}$	$\begin{pmatrix} 0.779 + i0.579, \\ 0.349 + i0.340 \end{pmatrix}$	$\begin{pmatrix} 0.471 + i0.339, \\ 0.548 + i0.629 \end{pmatrix}$	$\begin{pmatrix} 0.269 + i0.810, \\ 0.759 + i0.289 \end{pmatrix}$
P_5	$\begin{pmatrix} 0.380 + i0.570, \\ 0.761 + i0.520 \end{pmatrix}$	$\begin{pmatrix} 0.680 + i0.219, \\ 0.332 + i0.359 \end{pmatrix}$	$\begin{pmatrix} 0.248 + i0.369, \\ 0.759 + i0.583 \end{pmatrix}$	$\begin{pmatrix} 0.629 + i0.143, \\ 0.368 + i0.839 \end{pmatrix}$	$\begin{pmatrix} 0.438 + i0.258, \\ 0.549 + i0.719 \end{pmatrix}$
P_6	$\begin{pmatrix} 0.191 + i0.660, \\ 0.850 + i0.370 \end{pmatrix}$	$\begin{pmatrix} 0.829 + i0.780, \\ 0.168 + i0.122 \end{pmatrix}$	$\begin{pmatrix} 0.469 + i0.819, \\ 0.519 + i0.189 \end{pmatrix}$	$\begin{pmatrix} 0.541 + i0.629, \\ 0.278 + i0.288 \end{pmatrix}$	$\begin{pmatrix} 0.168 + i0.509, \\ 0.809 + i0.459 \end{pmatrix}$
P_7	$\begin{pmatrix} 0.050 + i0.751, \\ 0.710 + i0.280 \end{pmatrix}$	$\begin{pmatrix} 0.049 + i0.459, \\ 0.822 + i0.539 \end{pmatrix}$	$\begin{pmatrix} 0.339 + i0.689, \\ 0.669 + i0.343 \end{pmatrix}$	$\begin{pmatrix} 0.249 + i0.588, \\ 0.818 + i0.419 \end{pmatrix}$	$\begin{pmatrix} 0.968 + i0.468, \\ 0.209 + i0.418 \end{pmatrix}$
P_8	$\begin{pmatrix} 0.811 + i0.410, \\ 0.411 + i0.560 \end{pmatrix}$	$\begin{pmatrix} 0.868 + i0.349, \\ 0.410 + i0.609 \end{pmatrix}$	$\begin{pmatrix} 0.639 + i0.442, \\ 0.568 + i0.579 \end{pmatrix}$	$\begin{pmatrix} 0.039 + i0.268, \\ 0.679 + i0.709 \end{pmatrix}$	$\begin{pmatrix} 0.709 + i0.349, \\ 0.414 + i0.638 \end{pmatrix}$
P_9	$\begin{pmatrix} 0.369 + i0.589, \\ 0.589 + i0.470 \end{pmatrix}$	$\begin{pmatrix} 0.449 + i0.172, \\ 0.639 + i0.869 \end{pmatrix}$	$\begin{pmatrix} 0.089 + i0.522, \\ 0.819 + i0.479 \end{pmatrix}$	$\begin{pmatrix} 0.578 + i0.859, \\ 0.438 + i0.253 \end{pmatrix}$	$\begin{pmatrix} 0.408 + i0.679, \\ 0.579 + i0.378 \end{pmatrix}$
P_{10}	$\begin{pmatrix} 0.459 + i0.669, \\ 0.409 + i0.352 \end{pmatrix}$	$\begin{pmatrix} 0.279 + i0.439, \\ 0.590 + i0.609 \end{pmatrix}$	$\begin{pmatrix} 0.283 + i0.743, \\ 0.679 + i0.139 \end{pmatrix}$	$\begin{pmatrix} 0.809 + i0.459, \\ 0.348 + i0.508 \end{pmatrix}$	$\begin{pmatrix} 0.178 + i0.539, \\ 0.743 + i0.449 \end{pmatrix}$

Table 8. Temporal matrix 5.

	A_1	A_2	A_3	A_4	A_5
P_1	$\begin{pmatrix} 0.179 + i0.748, \\ 0.849 + i0.188 \end{pmatrix}$	$\begin{pmatrix} 0.239 + i0.188, \\ 0.778 + i0.479 \end{pmatrix}$	$\begin{pmatrix} 0.329 + i0.609, \\ 0.677 + i0.179 \end{pmatrix}$	$\begin{pmatrix} 0.549 + i0.293, \\ 0.418 + i0.658 \end{pmatrix}$	$\begin{pmatrix} 0.219 + i0.738, \\ 0.819 + i0.079 \end{pmatrix}$
P_2	$\begin{pmatrix} 0.349 + i0.633, \\ 0.648 + i0.519 \end{pmatrix}$	$\begin{pmatrix} 0.189 + i0.880, \\ 0.619 + i0.138 \end{pmatrix}$	$\begin{pmatrix} 0.269 + i0.368, \\ 0.748 + i0.388 \end{pmatrix}$	$\begin{pmatrix} 0.269 + i0.829, \\ 0.709 + i0.059 \end{pmatrix}$	$\begin{pmatrix} 0.579 + i0.219, \\ 0.409 + i0.659 \end{pmatrix}$
P_3	$\begin{pmatrix} 0.479 + i0.509, \\ 0.549 + i0.282 \end{pmatrix}$	$\begin{pmatrix} 0.760 + i0.649, \\ 0.269 + i0.338 \end{pmatrix}$	$\begin{pmatrix} 0.789 + i0.589, \\ 0.338 + i0.467 \end{pmatrix}$	$\begin{pmatrix} 0.358 + i0.749, \\ 0.679 + i0.159 \end{pmatrix}$	$\begin{pmatrix} 0.349 + i0.749, \\ 0.589 + i0.179 \end{pmatrix}$
P_4	$\begin{pmatrix} 0.268 + i0.469, \\ 0.379 + i0.378 \end{pmatrix}$	$\begin{pmatrix} 0.349 + i0.719, \\ 0.649 + i0.279 \end{pmatrix}$	$\begin{pmatrix} 0.512 + i0.279, \\ 0.489 + i0.582 \end{pmatrix}$	$\begin{pmatrix} 0.179 + i0.509, \\ 0.819 + i0.278 \end{pmatrix}$	$\begin{pmatrix} 0.409 + i0.868, \\ 0.619 + i0.219 \end{pmatrix}$
P_5	$\begin{pmatrix} 0.779 + i0.349, \\ 0.249 + i0.589 \end{pmatrix}$	$\begin{pmatrix} 0.468 + i0.339, \\ 0.619 + i0.609 \end{pmatrix}$	$\begin{pmatrix} 0.619 + i0.349, \\ 0.389 + i0.648 \end{pmatrix}$	$\begin{pmatrix} 0.749 + i0.619, \\ 0.239 + i0.368 \end{pmatrix}$	$\begin{pmatrix} 0.189 + i0.679, \\ 0.739 + i0.368 \end{pmatrix}$
P_6	$\begin{pmatrix} 0.529 + i0.168, \\ 0.409 + i0.679 \end{pmatrix}$	$\begin{pmatrix} 0.249 + i0.168, \\ 0.709 + i0.808 \end{pmatrix}$	$\begin{pmatrix} 0.439 + i0.743, \\ 0.549 + i0.279 \end{pmatrix}$	$\begin{pmatrix} 0.679 + i0.478, \\ 0.328 + i0.519 \end{pmatrix}$	$\begin{pmatrix} 0.679 + i0.509, \\ 0.189 + i0.409 \end{pmatrix}$
P_7	$\begin{pmatrix} 0.659 + i0.609, \\ 0.348 + i0.379 \end{pmatrix}$	$\begin{pmatrix} 0.519 + i0.238, \\ 0.449 + i0.709 \end{pmatrix}$	$\begin{pmatrix} 0.179 + i0.679, \\ 0.779 + i0.329 \end{pmatrix}$	$\begin{pmatrix} 0.439 + i0.279, \\ 0.549 + i0.709 \end{pmatrix}$	$\begin{pmatrix} 0.749 + i0.279, \\ 0.248 + i0.619 \end{pmatrix}$
P_8	$\begin{pmatrix} 0.809 + i0.268, \\ 0.209 + i0.739 \end{pmatrix}$	$\begin{pmatrix} 0.668 + i0.349, \\ 0.339 + i0.669 \end{pmatrix}$	$\begin{pmatrix} 0.819 + i0.139, \\ 0.288 + i0.738 \end{pmatrix}$	$\begin{pmatrix} 0.389 + i0.109, \\ 0.609 + i0.588 \end{pmatrix}$	$\begin{pmatrix} 0.819 + i0.438, \\ 0.079 + i0.579 \end{pmatrix}$
P_9	$\begin{pmatrix} 0.281 + i0.579, \\ 0.749 + i0.518 \end{pmatrix}$	$\begin{pmatrix} 0.488 + i0.519, \\ 0.268 + i0.609 \end{pmatrix}$	$\begin{pmatrix} 0.279 + i0.559, \\ 0.609 + i0.411 \end{pmatrix}$	$\begin{pmatrix} 0.859 + i0.319, \\ 0.189 + i0.659 \end{pmatrix}$	$\begin{pmatrix} 0.459 + i0.369, \\ 0.509 + i0.709 \end{pmatrix}$
P_{10}	$\begin{pmatrix} 0.349 + i0.439, \\ 0.559 + i0.488 \end{pmatrix}$	$\begin{pmatrix} 0.049 + i0.468, \\ 0.889 + i0.509 \end{pmatrix}$	$\begin{pmatrix} 0.159 + i0.409, \\ 0.508 + i0.619 \end{pmatrix}$	$\begin{pmatrix} 0.079 + i0.519, \\ 0.739 + i0.469 \end{pmatrix}$	$\begin{pmatrix} 0.579 + i0.189, \\ 0.438 + i0.819 \end{pmatrix}$

Step 2: The aggregated matrix, with the help of the Cq-ROFAAWA operator, is given in **Table 9**.

Table 9. Aggregated matrix.

	A ₁	A ₂	A ₃	A ₄	A ₅
P ₁	$\begin{pmatrix} 0.591 + i0.827, \\ 0.294 + i0.147 \end{pmatrix}$	$\begin{pmatrix} 0.549 + i0.621, \\ 0.391 + i0.204 \end{pmatrix}$	$\begin{pmatrix} 0.761 + i0.766, \\ 0.262 + i0.138 \end{pmatrix}$	$\begin{pmatrix} 0.690 + i0.565, \\ 0.198 + i0.280 \end{pmatrix}$	$\begin{pmatrix} 0.549 + i0.765, \\ 0.388 + i0.060 \end{pmatrix}$
P ₂	$\begin{pmatrix} 0.423 + i0.678, \\ 0.413 + i0.248 \end{pmatrix}$	$\begin{pmatrix} 0.643 + i0.832, \\ 0.248 + i0.086 \end{pmatrix}$	$\begin{pmatrix} 0.640 + i0.741, \\ 0.351 + i0.177 \end{pmatrix}$	$\begin{pmatrix} 0.520 + i0.843, \\ 0.332 + i0.054 \end{pmatrix}$	$\begin{pmatrix} 0.542 + i0.579, \\ 0.362 + i0.260 \end{pmatrix}$
P ₃	$\begin{pmatrix} 0.837 + i0.627, \\ 0.233 + i0.214 \end{pmatrix}$	$\begin{pmatrix} 0.813 + i0.758, \\ 0.165 + i0.144 \end{pmatrix}$	$\begin{pmatrix} 0.816 + i0.606, \\ 0.260 + i0.198 \end{pmatrix}$	$\begin{pmatrix} 0.688 + i0.775, \\ 0.316 + i0.161 \end{pmatrix}$	$\begin{pmatrix} 0.729 + i0.645, \\ 0.182 + i0.215 \end{pmatrix}$
P ₄	$\begin{pmatrix} 0.748 + i0.678, \\ 0.110 + i0.201 \end{pmatrix}$	$\begin{pmatrix} 0.515 + i0.756, \\ 0.308 + i0.164 \end{pmatrix}$	$\begin{pmatrix} 0.717 + i0.562, \\ 0.211 + i0.228 \end{pmatrix}$	$\begin{pmatrix} 0.812 + i0.737, \\ 0.247 + i0.165 \end{pmatrix}$	$\begin{pmatrix} 0.642 + i0.896, \\ 0.213 + i0.100 \end{pmatrix}$
P ₅	$\begin{pmatrix} 0.740 + i0.684, \\ 0.210 + i0.221 \end{pmatrix}$	$\begin{pmatrix} 0.809 + i0.636, \\ 0.106 + i0.229 \end{pmatrix}$	$\begin{pmatrix} 0.644 + i0.665, \\ 0.276 + i0.232 \end{pmatrix}$	$\begin{pmatrix} 0.775 + i0.586, \\ 0.138 + i0.337 \end{pmatrix}$	$\begin{pmatrix} 0.639 + i0.665, \\ 0.316 + i0.230 \end{pmatrix}$
P ₆	$\begin{pmatrix} 0.685 + i0.619, \\ 0.288 + i0.227 \end{pmatrix}$	$\begin{pmatrix} 0.784 + i0.866, \\ 0.165 + i0.109 \end{pmatrix}$	$\begin{pmatrix} 0.590 + i0.889, \\ 0.304 + i0.064 \end{pmatrix}$	$\begin{pmatrix} 0.667 + i0.816, \\ 0.137 + i0.120 \end{pmatrix}$	$\begin{pmatrix} 0.836 + i0.777, \\ 0.191 + i0.156 \end{pmatrix}$
P ₇	$\begin{pmatrix} 0.634 + i0.794, \\ 0.263 + i0.135 \end{pmatrix}$	$\begin{pmatrix} 0.667 + i0.733, \\ 0.338 + i0.260 \end{pmatrix}$	$\begin{pmatrix} 0.636 + i0.822, \\ 0.275 + i0.079 \end{pmatrix}$	$\begin{pmatrix} 0.515 + i0.663, \\ 0.421 + i0.218 \end{pmatrix}$	$\begin{pmatrix} 0.946 + i0.525, \\ 0.045 + i0.281 \end{pmatrix}$
P ₈	$\begin{pmatrix} 0.903 + i0.712, \\ 0.068 + i0.271 \end{pmatrix}$	$\begin{pmatrix} 0.812 + i0.669, \\ 0.225 + i0.245 \end{pmatrix}$	$\begin{pmatrix} 0.787 + i0.447, \\ 0.168 + i0.384 \end{pmatrix}$	$\begin{pmatrix} 0.813 + i0.358, \\ 0.206 + i0.422 \end{pmatrix}$	$\begin{pmatrix} 0.818 + i0.617, \\ 0.084 + i0.234 \end{pmatrix}$
P ₉	$\begin{pmatrix} 0.501 + i0.708, \\ 0.369 + i0.217 \end{pmatrix}$	$\begin{pmatrix} 0.771 + i0.690, \\ 0.159 + i0.238 \end{pmatrix}$	$\begin{pmatrix} 0.502 + i0.743, \\ 0.273 + i0.166 \end{pmatrix}$	$\begin{pmatrix} 0.863 + i0.837, \\ 0.117 + i0.146 \end{pmatrix}$	$\begin{pmatrix} 0.754 + i0.633, \\ 0.188 + i0.278 \end{pmatrix}$
P ₁₀	$\begin{pmatrix} 0.601 + i0.639, \\ 0.252 + i0.214 \end{pmatrix}$	$\begin{pmatrix} 0.568 + i0.611, \\ 0.280 + i0.226 \end{pmatrix}$	$\begin{pmatrix} 0.623 + i0.786, \\ 0.255 + i0.100 \end{pmatrix}$	$\begin{pmatrix} 0.534 + i0.558, \\ 0.287 + i0.305 \end{pmatrix}$	$\begin{pmatrix} 0.505 + i0.560, \\ 0.400 + i0.357 \end{pmatrix}$

Step 3: Attributes are of benefit type, so the normalized matrix remains the same as the aggregated matrix.

Step 4: Determination of attribute weights using the CRITIC method.

Step 4.1: The associated score matrix of the normalized Cq-ROF matrix is given as:

$$E_{cd} = \begin{bmatrix} 0.6857 & 0.5843 & 0.7175 & 0.6198 & 0.6387 \\ 0.5755 & 0.7064 & 0.6549 & 0.6756 & 0.5722 \\ 0.7029 & 0.7413 & 0.6853 & 0.6887 & 0.6601 \\ 0.6803 & 0.6338 & 0.6313 & 0.7291 & 0.7437 \\ 0.6760 & 0.6931 & 0.6321 & 0.6563 & 0.6276 \\ 0.6308 & 0.7817 & 0.7200 & 0.7091 & 0.7608 \\ 0.6839 & 0.6588 & 0.6982 & 0.5859 & 0.7425 \\ 0.7693 & 0.7024 & 0.6289 & 0.6247 & 0.6922 \\ 0.6050 & 0.6924 & 0.6280 & 0.8060 & 0.6637 \\ 0.6868 & 0.5946 & 0.6777 & 0.5685 & 0.5486 \end{bmatrix}$$

Step 4.2: The correlation coefficient matrix is given as:

$$\epsilon_{gh} = \begin{bmatrix} 1.0000 & -0.2205 & -0.0417 & -0.5143 & 0.1977 \\ -0.2205 & 1.0000 & -0.0171 & 0.4573 & 0.3560 \\ -0.0417 & -0.0171 & 1.0000 & -0.3813 & 0.1442 \\ -0.5143 & 0.4573 & -0.3813 & 1.0000 & 0.2929 \\ 0.1977 & 0.3560 & 0.1442 & 0.2929 & 1.0000 \end{bmatrix}$$

Step 4.3: The standard deviation of each attribute is given as:

$$S_1 = 0.0515, S_2 = 0.0589, S_3 = 0.0352, S_4 = 0.0678, S_5 = 0.0681$$

Step 4.4: The amount of information corresponding to each attribute is determined and given as:

$$\bar{V}_1 = 0.2357, \bar{V}_2 = 0.2015, \bar{V}_3 = 0.1512, \bar{V}_4 = 0.2809, \bar{V}_5 = 0.2049$$

Step 4.5: Attribute weights are given as:

$$\bar{w}_1 = 0.2194, \bar{w}_2 = 0.1876, \bar{w}_3 = 0.1407, \bar{w}_4 = 0.2615, \bar{w}_5 = 0.1908$$

Step 5: Now, to rank the alternatives, we use the WASPAS technique.

Steps 5.1 & 5.2: WSM and WPM are given in **Table 10**.

Table 10. WSM and WPM.

$\bar{Q}_c^1$	Weighted sum modal	$\bar{Q}_c^2$	Weighted product modal
$\bar{Q}_1^1$	(0.7923 + ι 0.8728, 0.0656 + ι 0.0148)	$\bar{Q}_1^2$	(0.0048 + ι 0.0065, 0.9942 + ι 0.9901)
$\bar{Q}_2^1$	(0.7080 + ι 0.8997, 0.0890 + ι 0.0117)	$\bar{Q}_2^2$	(0.0035 + ι 0.0078, 0.9950 + ι 0.9894)
$\bar{Q}_3^1$	(0.9155 + ι 0.8463, 0.0369 + ι 0.0229)	$\bar{Q}_3^2$	(0.0088 + ι 0.0062, 0.9927 + ι 0.9912)
$\bar{Q}_4^1$	(0.8611 + ι 0.9006, 0.0296 + ι 0.0180)	$\bar{Q}_4^2$	(0.0064 + ι 0.0077, 0.9921 + ι 0.9905)
$\bar{Q}_5^1$	(0.8790 + ι 0.7972, 0.0247 + ι 0.0455)	$\bar{Q}_5^2$	(0.0072 + ι 0.0051, 0.9916 + ι 0.9933)
$\bar{Q}_6^1$	(0.8763 + ι 0.9360, 0.0287 + ι 0.0102)	$\bar{Q}_6^2$	(0.0069 + ι 0.0098, 0.9920 + ι 0.9886)
$\bar{Q}_7^1$	(0.8992 + ι 0.8727, 0.0341 + ι 0.0222)	$\bar{Q}_7^2$	(0.0064 + ι 0.0066, 0.9931 + ι 0.9913)
$\bar{Q}_8^1$	(0.9501 + ι 0.7472, 0.0115 + ι 0.0703)	$\bar{Q}_8^2$	(0.0119 + ι 0.0038, 0.9891 + ι 0.9944)
$\bar{Q}_9^1$	(0.8809 + ι 0.8814, 0.0280 + ι 0.0286)	$\bar{Q}_9^2$	(0.0067 + ι 0.0073, 0.9920 + ι 0.9919)
$\bar{Q}_{10}^1$	(0.7134 + ι 0.7918, 0.0640 + ι 0.0374)	$\bar{Q}_{10}^2$	(0.0038 + ι 0.0047, 0.9942 + ι 0.9929)

Step 5.3: The WASPAS index is given in **Table 11**.

Table 11. WASPAS index.

$\bar{Q}_c$	WASPAS index
$\bar{Q}_1$	(0.7276 + ι 0.8136, 0.1452 + ι 0.0506)
$\bar{Q}_2$	(0.6435 + ι 0.8443, 0.1801 + ι 0.0427)
$\bar{Q}_3$	(0.8637 + ι 0.7843, 0.0965 + ι 0.0689)
$\bar{Q}_4$	(0.8006 + ι 0.8454, 0.0825 + ι 0.0581)
$\bar{Q}_5$	(0.8205 + ι 0.7327, 0.0725 + ι 0.1119)
$\bar{Q}_6$	(0.8174 + ι 0.8890, 0.0808 + ι 0.0388)
$\bar{Q}_7$	(0.8438 + ι 0.8134, 0.0913 + ι 0.0674)
$\bar{Q}_8$	(0.9077 + ι 0.6821, 0.0421 + ι 0.1524)
$\bar{Q}_9$	(0.8226 + ι 0.8233, 0.0794 + ι 0.0805)
$\bar{Q}_{10}$	(0.6488 + ι 0.7271, 0.1426 + ι 0.0974)

Where $\lambda = 0.5$.

Step 5.4: Scores of alternatives are:

$$\S(\mathbb{P}_1) = 0.73013, \S(\mathbb{P}_2) = 0.71561, \S(\mathbb{P}_3) = 0.78114, \S(\mathbb{P}_4) = 0.77914, \S(\mathbb{P}_5) = 0.73596$$

$$\S(\mathbb{P}_6) = 0.81201, \S(\mathbb{P}_7) = 0.78449, \S(\mathbb{P}_8) = 0.76540, \S(\mathbb{P}_9) = 0.77841, \S(\mathbb{P}_{10}) = 0.66343$$

Since,

$$\S(\mathbb{P}_6) > \S(\mathbb{P}_7) > \S(\mathbb{P}_3) > \S(\mathbb{P}_4) > \S(\mathbb{P}_9) > \S(\mathbb{P}_8) > \S(\mathbb{P}_5) > \S(\mathbb{P}_1) > \S(\mathbb{P}_2) > \S(\mathbb{P}_{10})$$

So $\mathbb{P}_6$ is the best alternative.

The scores of alternatives are shown in **Figure 5**.

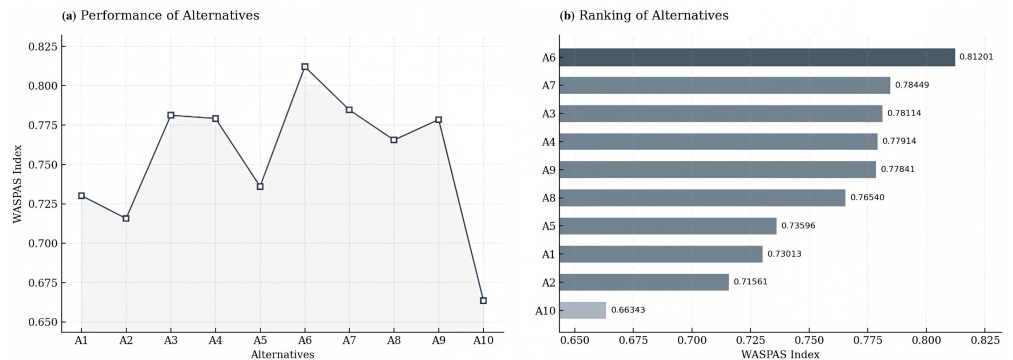


Figure 5. Alternatives scores.

6.3. Sensitivity analysis

The sensitivity analysis is done extensively to evaluate the soundness of the proposed temporal-conscious CRITIC-WASPAS framework to the main parameters: λ (the relative importance parameter in WASPAS), q (the q-rung parameter in Cq-ROFSs), and κ (the aggregation operator tuning parameter). By varying each parameter within realistic ranges while keeping others constant, the study examines the impact on the ranking of energy planning alternatives. The findings show that the exact order of ranking does not change significantly, but it has slight variations when the parameters vary significantly, which serves to show that the framework is very robust to variations in the values of λ , q , and κ . This demonstrates the robustness and stability of the proposed methodology in the case of uncertainty and time dynamics, such that the outcomes of the decision-making process when using different parameter configurations yield similar results.

The score values of alternatives under different values of λ are shown in **Table 12**.

Table 12. Score values of alternatives under different values of λ .

Variations of λ	Score values									
Operators	$\$ (\mathbb{P}_1)$	$\$ (\mathbb{P}_2)$	$\$ (\mathbb{P}_3)$	$\$ (\mathbb{P}_4)$	$\$ (\mathbb{P}_5)$	$\$ (\mathbb{P}_6)$	$\$ (\mathbb{P}_7)$	$\$ (\mathbb{P}_8)$	$\$ (\mathbb{P}_9)$	$\$ (\mathbb{P}_{10})$
Cq – ROFAAWA $_{\lambda=0.1}$	0.5989	0.5884	0.6387	0.6396	0.6052	0.6675	0.6407	0.6309	0.6361	0.5530
Cq – ROFAAWA $_{\lambda=0.2}$	0.6556	0.6446	0.7005	0.6990	0.6618	0.7296	0.7027	0.6914	0.6973	0.6026
Cq – ROFAAWA $_{\lambda=0.3}$	0.6881	0.6761	0.7358	0.7338	0.6940	0.7658	0.7384	0.7247	0.7326	0.6293
Cq – ROFAAWA $_{\lambda=0.4}$	0.7115	0.6983	0.7612	0.7591	0.7174	0.7918	0.7642	0.7478	0.7582	0.6483
Cq – ROFAAWA $_{\lambda=0.5}$	0.7301	0.7157	0.7811	0.7791	0.7360	0.8120	0.7845	0.7654	0.7784	0.6634
Cq – ROFAAWA $_{\lambda=0.6}$	0.7457	0.7299	0.7975	0.7957	0.7515	0.8285	0.8012	0.7797	0.7951	0.6763
Cq – ROFAAWA $_{\lambda=0.7}$	0.7590	0.7421	0.8114	0.8098	0.7649	0.8422	0.8154	0.7916	0.8093	0.6875
Cq – ROFAAWA $_{\lambda=0.8}$	0.7707	0.7527	0.8234	0.8219	0.7766	0.8540	0.8277	0.8018	0.8216	0.6975
Cq – ROFAAWA $_{\lambda=0.9}$	0.7811	0.7621	0.8340	0.8327	0.7870	0.8642	0.8384	0.8108	0.8324	0.7065

Ranking of alternatives under different values of λ is shown in **Table 13**.

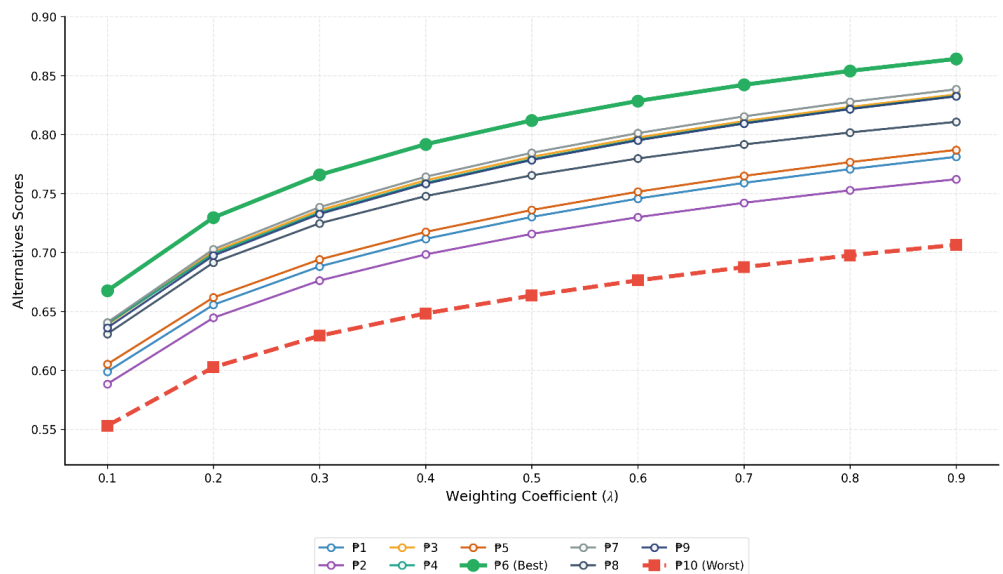
Table 13. Ranking of alternatives under different values of λ .

Cq-ROFAAWA operators	Ranking
Cq – ROFAAWA $_{\lambda=0.1}$	$\mathbb{P}_6 > \mathbb{P}_7 > \mathbb{P}_4 > \mathbb{P}_3 > \mathbb{P}_9 > \mathbb{P}_8 > \mathbb{P}_5 > \mathbb{P}_1 > \mathbb{P}_2 > \mathbb{P}_{10}$
Cq – ROFAAWA $_{\lambda=0.2}$	$\mathbb{P}_6 > \mathbb{P}_7 > \mathbb{P}_3 > \mathbb{P}_4 > \mathbb{P}_9 > \mathbb{P}_8 > \mathbb{P}_5 > \mathbb{P}_1 > \mathbb{P}_2 > \mathbb{P}_{10}$
Cq – ROFAAWA $_{\lambda=0.3}$	$\mathbb{P}_6 > \mathbb{P}_7 > \mathbb{P}_3 > \mathbb{P}_4 > \mathbb{P}_9 > \mathbb{P}_8 > \mathbb{P}_5 > \mathbb{P}_1 > \mathbb{P}_2 > \mathbb{P}_{10}$

Table 13. *Cont.*

Cq-ROFAAWA operators	Ranking
Cq – ROFAAWA $_{\lambda=0.4}$	$P_6 > P_7 > P_3 > P_4 > P_9 > P_8 > P_5 > P_1 > P_2 > P_{10}$
Cq – ROFAAWA $_{\lambda=0.5}$	$P_6 > P_7 > P_3 > P_4 > P_9 > P_8 > P_5 > P_1 > P_2 > P_{10}$
Cq – ROFAAWA $_{\lambda=0.6}$	$P_6 > P_7 > P_3 > P_4 > P_9 > P_8 > P_5 > P_1 > P_2 > P_{10}$
Cq – ROFAAWA $_{\lambda=0.7}$	$P_6 > P_7 > P_3 > P_4 > P_9 > P_8 > P_5 > P_1 > P_2 > P_{10}$
Cq – ROFAAWA $_{\lambda=0.8}$	$P_6 > P_7 > P_3 > P_4 > P_9 > P_8 > P_5 > P_1 > P_2 > P_{10}$
Cq – ROFAAWA $_{\lambda=0.9}$	$P_6 > P_7 > P_3 > P_4 > P_9 > P_8 > P_5 > P_1 > P_2 > P_{10}$

Variations in alternative scores under different values of λ are shown in **Figure 6**.

**Figure 6.** Variation under weighting constant λ .

The score values of alternatives under different values of q are shown in **Table 14**.

Table 14. Score values of alternatives under different values of q .

Variations of q	Score values									
Operators	$S(P_1)$	$S(P_2)$	$S(P_3)$	$S(P_4)$	$S(P_5)$	$S(P_6)$	$S(P_7)$	$S(P_8)$	$S(P_9)$	$S(P_{10})$
Cq – ROFAAWA $_{q=3}$	0.7301	0.7156	0.7811	0.7791	0.7360	0.8120	0.7845	0.7654	0.7784	0.6634
Cq – ROFAAWA $_{q=4}$	0.6606	0.6508	0.7115	0.7103	0.6609	0.7436	0.7168	0.7059	0.7052	0.5981
Cq – ROFAAWA $_{q=5}$	0.6139	0.6073	0.6600	0.6606	0.6103	0.6904	0.6688	0.6624	0.6520	0.5595
Cq – ROFAAWA $_{q=6}$	0.5826	0.5779	0.6222	0.6246	0.5765	0.6497	0.6350	0.6297	0.6140	0.5368
Cq – ROFAAWA $_{q=7}$	0.5612	0.5576	0.5943	0.5980	0.5538	0.6188	0.6108	0.6045	0.5867	0.5231
Cq – ROFAAWA $_{q=8}$	0.5464	0.5432	0.5735	0.5782	0.5383	0.5951	0.5932	0.5845	0.5666	0.5147
Cq – ROFAAWA $_{q=9}$	0.5357	0.5329	0.5577	0.5630	0.5276	0.5769	0.5800	0.5687	0.5518	0.5095

The ranking of alternatives under different values of q is shown in **Table 15**.

Table 15. Ranking of alternatives under different values of q .

Cq-ROFAAWA operators	Ranking
Cq – ROFAAWA $_{q=3}$	$P_6 > P_7 > P_3 > P_4 > P_9 > P_8 > P_5 > P_1 > P_2 > P_{10}$
Cq – ROFAAWA $_{q=4}$	$P_6 > P_7 > P_3 > P_4 > P_8 > P_9 > P_5 > P_1 > P_2 > P_{10}$
Cq – ROFAAWA $_{q=5}$	$P_6 > P_7 > P_8 > P_4 > P_3 > P_9 > P_1 > P_5 > P_2 > P_{10}$
Cq – ROFAAWA $_{q=6}$	$P_6 > P_7 > P_8 > P_4 > P_3 > P_9 > P_1 > P_2 > P_5 > P_{10}$
Cq – ROFAAWA $_{q=7}$	$P_6 > P_7 > P_8 > P_4 > P_3 > P_9 > P_1 > P_2 > P_5 > P_{10}$
Cq – ROFAAWA $_{q=8}$	$P_6 > P_7 > P_8 > P_4 > P_3 > P_9 > P_1 > P_2 > P_5 > P_{10}$
Cq – ROFAAWA $_{q=9}$	$P_7 > P_6 > P_8 > P_4 > P_3 > P_9 > P_1 > P_2 > P_5 > P_{10}$

Variations in alternative scores under different values of q are shown in **Figure 7**.

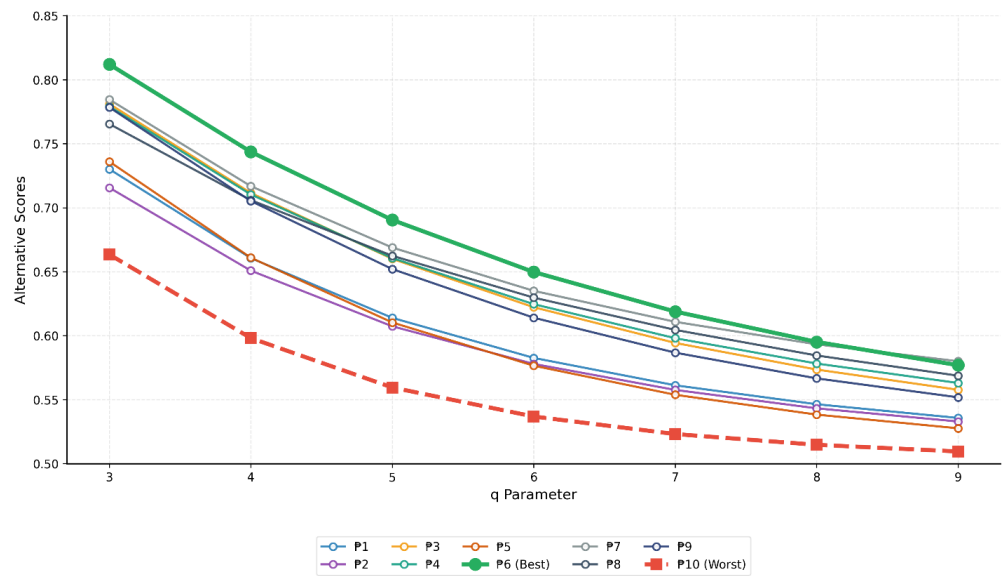


Figure 7. Variation under parameter q .

The score values of alternatives under different values of κ are shown in **Table 16**.

Table 16. Score values of alternatives under different values of κ .

Variations of κ	Score values									
Operators	$\$ (P_1)$	$\$ (P_2)$	$\$ (P_3)$	$\$ (P_4)$	$\$ (P_5)$	$\$ (P_6)$	$\$ (P_7)$	$\$ (P_8)$	$\$ (P_9)$	$\$ (P_{10})$
Cq – ROFAAWA $_{\kappa=2}$	0.7301	0.7156	0.7811	0.7791	0.7360	0.8120	0.7845	0.7654	0.7784	0.6634
Cq – ROFAAWA $_{\kappa=3}$	0.8462	0.8196	0.8939	0.8953	0.8510	0.9215	0.9011	0.8626	0.8930	0.7680
Cq – ROFAAWA $_{\kappa=5}$	0.9294	0.8970	0.9601	0.9640	0.9326	0.9762	0.9677	0.9258	0.9619	0.8625
Cq – ROFAAWA $_{\kappa=8}$	0.9627	0.9324	0.9817	0.9853	0.9647	0.9908	0.9875	0.9533	0.9840	0.9108
Cq – ROFAAWA $_{\kappa=12}$	0.9758	0.9488	0.9892	0.9921	0.9773	0.9952	0.9935	0.9659	0.9912	0.9338
Cq – ROFAAWA $_{\kappa=17}$	0.9819	0.9572	0.9923	0.9948	0.9831	0.9969	0.9958	0.9722	0.9941	0.9457
Cq – ROFAAWA $_{\kappa=23}$	0.9851	0.9621	0.9939	0.9961	0.9861	0.9977	0.9969	0.9759	0.9955	0.9525
Cq – ROFAAWA $_{\kappa=30}$	0.9869	0.9651	0.9948	0.9968	0.9879	0.9981	0.9975	0.9781	0.9963	0.9568

The ranking of alternatives under different values of κ is shown in **Table 17**.

Table 17. Ranking of alternatives under different values of κ .

Cq-ROFAAWA operators	Ranking
Cq – ROFAAWA $_{\kappa=2}$	$P_6 > P_7 > P_4 > P_3 > P_9 > P_8 > P_5 > P_1 > P_2 > P_{10}$
Cq – ROFAAWA $_{\kappa=3}$	$P_6 > P_7 > P_4 > P_3 > P_9 > P_8 > P_5 > P_1 > P_2 > P_{10}$
Cq – ROFAAWA $_{\kappa=5}$	$P_6 > P_7 > P_9 > P_4 > P_3 > P_8 > P_5 > P_1 > P_2 > P_{10}$
Cq – ROFAAWA $_{\kappa=8}$	$P_6 > P_7 > P_4 > P_9 > P_3 > P_5 > P_1 > P_8 > P_{10} > P_2$
Cq – ROFAAWA $_{\kappa=12}$	$P_6 > P_7 > P_4 > P_9 > P_3 > P_5 > P_1 > P_8 > P_2 > P_{10}$
Cq – ROFAAWA $_{\kappa=17}$	$P_7 > P_6 > P_4 > P_9 > P_3 > P_5 > P_1 > P_8 > P_2 > P_{10}$
Cq – ROFAAWA $_{\kappa=23}$	$P_7 > P_6 > P_4 > P_9 > P_3 > P_5 > P_8 > P_1 > P_2 > P_{10}$
Cq – ROFAAWA $_{\kappa=30}$	$P_7 > P_6 > P_4 > P_9 > P_3 > P_5 > P_8 > P_1 > P_2 > P_{10}$

Variations in alternative scores under different values of κ are shown in **Figure 8**.

The sensitivity analysis demonstrates that the proposed framework exhibits a satisfactory degree of stability under variations of λ , q , and κ . The WASPAS balancing coefficient (λ) has only a marginal influence on the ranking results, whereas moderate ranking changes are observed for higher values of the Aczel–Alsina parameter (κ)

and the q -rung parameter (q). In particular, $\mathbb{P}_7$ replaces $\mathbb{P}_6$ as the highest-ranked alternative for $\kappa = 17, 23$, and 30 , as well as for $q = 9$, while a few intermediate alternatives also exchange positions due to their closely competing appraisal scores. These observations indicate that the proposed framework is reasonably robust rather than completely insensitive to parameter variations. The ability of the model to reflect parameter-dependent changes provides additional flexibility for representing different uncertainty and aggregation preferences in practical decision-making problems.

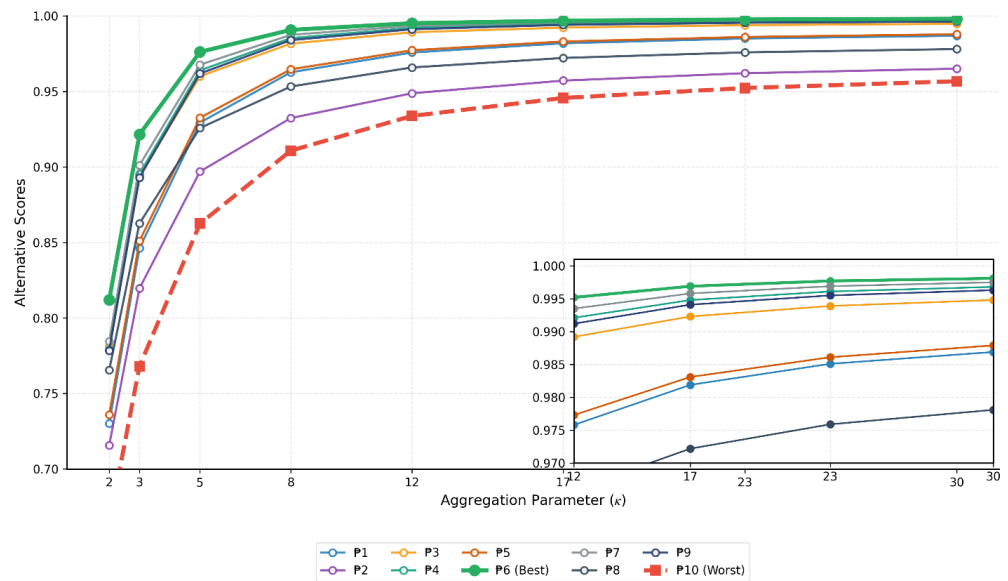


Figure 8. Variation under parameter κ .

7. Comparative analysis

In order to prove the efficiency and theoretical development of the given framework, it is important to make a comparison between it and the proven methods presented in the literature. It is not possible to make a direct numerical comparison between the fuzzy, IF, PF, q -ROF, and C q -ROF frameworks because each has a different information domain and constraint structure. C q -ROFS uses different dimensions to represent uncertainty than conventional fuzzy models, and the same numerical evaluations are dissimilar. Thus, the same number cannot be used for all frameworks to give a mathematically fair comparison. Therefore, the effectiveness of the proposed framework is evaluated by comparative ranking analysis and consistency measures instead of comparing with numerical scores. This kind of comparison will help understand the shortcomings of the current models and underscore the novelty of the contributions that are made by the proposed Temporal-Aware C q -ROF-CRITIC-WASPAS framework. The benchmark methods that could be used are the following:

- Theory of fuzzy CRITIC-WASPAS (F-CRITIC-WASPAS) by Zhou and Yang [10].
- Theory of intuitionistic fuzzy WASPAS (IF-WASPAS) by Stanujkić and Karabašević [37].
- Theory of Pythagorean Fuzzy WASPAS (PF-WASPAS) by Kahraman et al. [38].
- Theory of q -rung orthopair fuzzy CRITIC-WASPAS (q -ROF-CRITIC-WASPAS)

by Mardani and Saberi [39].

- Theory of complex q-rung orthopair fuzzy (Cq-ROF) aggregation theory by Liu et al. [40].

Comparison of existing theories with the proposed work is shown in **Figure 9**.

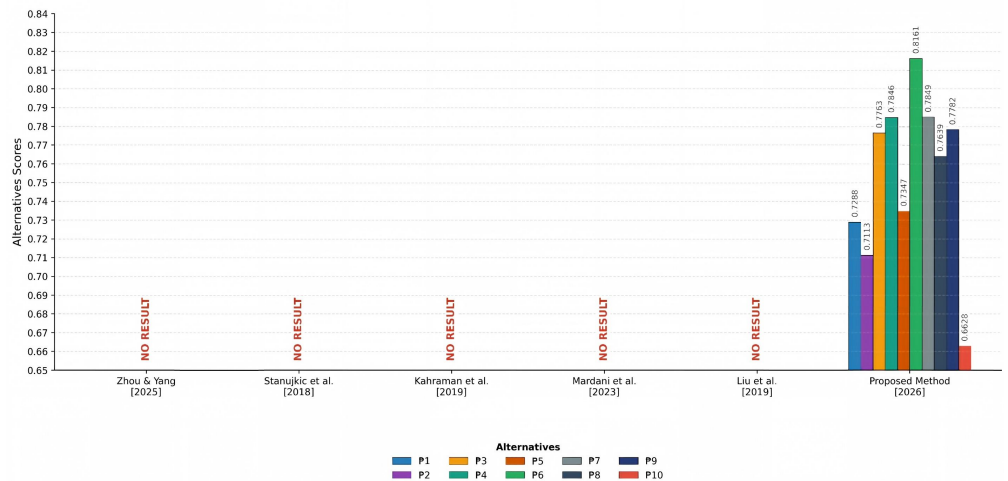


Figure 9. Comparative analysis of proposed work with existing theories.

Zhou and Yang [10] introduced an F-CRITIC-WASPAS model that integrates the CRITIC objective weighting approach and the WASPAS ranking procedure, which is an effective decision-making tool in a classical fuzzy environment. Its capability is, however, limited, as it merely considers membership degrees and does not explicitly consider non-membership or hesitation information. It is therefore not suitable for modelling complex and conflicting decision scenarios, which are often encountered in future energy planning. The model of IF-WASPAS proposed by Stanujkić and Karabašević [37] is an extension of the classical fuzzy framework, which considers both membership and non-membership degrees of fuzziness, and therefore enables a better representation of uncertainty. However, $\overline{M}^m + \overline{N}^m \leq 1$ is a relatively stringent requirement on the allowable decision space. Consequently, its flexibility is reduced if it is a decision with uncertain and inconsistent decision information. Another extension of the IF constraint, which enlarges the feasible decision space, was proposed by Kahraman et al. [38] as PF-WASPAS. This is more flexible than IFSs for the representation of uncertainty. But it should be noted that PFSs are still a special case of q-ROFSs where $q = 2$. So, their representation of uncertainty is even more limited than the generalized q-ROF environment, especially when higher q values are needed to handle the greater uncertainty. Mardani and Saberi [39] have proposed the q-ROF-CRITIC-WASPAS model, which uses an adjustable q parameter that makes it possible to increase the admissible region of membership and non-membership degrees, as the complexity of a decision problem grows. Moreover, it combines objective attribute weighting, which is realized by CRITIC, with the hybrid ranking function of WASPAS. The framework is, however, expressed in a real-world setting where it cannot fully capture multidimensional uncertainty. Moreover, it does not consider temporal variations that can change over time and evaluates in a single decision period. Liu et al. [40] introduced the Cq-ROF aggregation theory, which

has extended q-ROFSs to the complex domain by using an exponential representation of the unit circle. This allows the modelling of further uncertainty information with the addition of phase terms. However, the proposed aggregation model takes into account the issue of aggregation of information without considering an objective attribute weighting mechanism (like CRITIC), a hybrid ranking mechanism (like WASPAS), or a temporal evaluation mechanism. Furthermore, the Cartesian proposed representation of the membership and non-membership grades can be expressed in the unit square, which is more flexible to represent complex valued information compared to the exponential representation, where the information is confined to the unit circle. The proposed Temporal-Aware Cq-ROF-AA-CRITIC-WASPAS framework, however, embeds several complementary parts in a single decision-making system. First, the Cartesian Cq-ROF representation allows modeling two-dimensional uncertainty by using complex-valued membership and non-membership grades. Second, the proposed aggregation operators (Aczel–Alsina) offer a flexible information fusion mechanism in the Cq-ROF environment. Thirdly, the attribute weights determined by the CRITIC method are objective values that can be obtained by minimizing the subjectivity of the attribute weight assignment process, taking into account the contrast intensity and the inter-criteria correlation. Fourth, the WASPAS method has the combined merits of the Weighted Sum Model (WSM) and the Weighted Product Model (WPM), thereby achieving a stable and discriminative ranking performance. Finally, the proposed framework includes multiple temporal decision matrices in a temporal weighting strategy that enables the evaluation from various periods to be combined and emphasizes more the more recent information, as compared to the existing comparative approaches. This combination allows for a more complete characterization of uncertainty and allows for a systematic process to make decisions in future energy planning.

8. Conclusion

This paper presents a temporal-aware Cq-ROF-CRITIC-WASPAS framework as a powerful and flexible decision support framework in future energy planning under uncertainty. The framework harnesses the multidimensional uncertainties, time-dependence, and hesitation in experts by utilizing Cq-ROFSs, which address the weaknesses of conventional fuzzy systems and MCDM. CRITIC weighting provides objective prioritization of criteria depending on contrast intensity and interdependencies, and WASPAS ranking offers clear, discriminative, and interpretable evaluation of the various energy strategies. The framework has been shown to perform better in balancing economic, environmental, technological, and socio-political aspects, and allows policymakers to make resilient, efficient, and sustainable energy choices by policymakers.

Key contributions include:

- Advanced Cq-ROF aggregation operators that model complex temporal and uncertain expert judgments with high reliability.
- A systematic, temporal-aware MCDM framework integrating Cq-ROF, CRITIC,

and WASPAS for holistic evaluation of energy strategies.

- Demonstrated superiority over conventional fuzzy and q-ROF approaches, offering enhanced robustness, interpretability, and decision-making accuracy in future energy planning.

8.1. Limitations

While the proposed framework is promising, the following limitations need to be recognized. First, the proposed methodology is validated with a hypothetical temporal case study in order to prove that it is mathematically applicable, but not with real temporal datasets. Hence, its applicability in actual decision-making situations needs to be explored further. Second, the proposed framework comprises several computational phases such as temporal aggregation, Aczel–Alsina operations, CRITIC weighting, and WASPAS ranking, which can lead to a higher computational complexity, especially for large-scale decision-making problems with a high number of alternatives, criteria, and temporal periods.

8.2. Future research directions

Further studies in the future could be directed towards verifying the proposed framework with real-world temporal datasets from future energy planning and other real-world decision-making applications. In addition, there may be opportunities to create specialized software tools or computational algorithms that enhance the computational efficiency of the proposed approach. The incorporation of machine learning and artificial intelligence techniques could potentially aid in parameter estimation, automate the decision-making process, and decrease the computational load, potentially making the proposed framework more appropriate for large-scale and real-time decision-making scenarios. The suggested framework can be integrated with Physics-Informed Neural Networks (PINNs) in the future to enhance the prediction and decision-making in energy planning. Recent work has demonstrated the efficacy of PINNs for the modeling of complicated systems in the presence of uncertainty [41,42].

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AI use statement: The authors declare that no artificial intelligence (AI) tools were used in the preparation of the originally submitted manuscript.

Abbreviations

CRITIC	Criteria Importance Through Intercriteria Correlation
WASPAS	Weighted Aggregated Sum Product Assessment
AA	Aczel–Alsina
MCDM	Multi-Criteria Decision Making
FSs	Fuzzy Sets
IFSs	Intuitionistic Fuzzy Sets
PFSs	Pythagorean Fuzzy Sets
q-ROFSs	q-Rung Orthopair Fuzzy Sets
Cq-ROFSs	Complex q-Rung Orthopair Fuzzy Sets
Cq-ROFNs	Complex q-Rung Orthopair Fuzzy Numbers
Cq-ROFAAWA	Complex q-Rung Orthopair Fuzzy Aczel–Alsina Weightage Average Operator
Cq-ROFAAWG	Complex q-Rung Orthopair Fuzzy Aczel–Alsina Weightage Geometric Operator
WSM	Weighted Sum Model
WPM	Weighted Product Model
$\overline{M}^{\overbrace{m-re}}$	Real membership grade
$\overline{M}^{\overbrace{m-im}}$	Imaginary membership grade
$\overline{M}^{\overbrace{m-re}}$	Real non-membership grade
$\overline{M}^{\overbrace{m-im}}$	Imaginary non-membership grade

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