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Article

Evaluating sustainable energy alternatives for Haryana's energy transition through an integrated decision-making approach

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Abstract: The development of sustainable energy sources is one of the most significant issues facing policymakers who need to strike a balance between energy demand, environmental sustainability and economic development. In this respect, much uncertainty, fuzziness, and inaccurate data often come into play in decision-making and thus standardized evaluation methods are less practical in the evaluation of complex energy options. Thus, this paper suggests a multi-criteria decision-making model that is integrated with q-rung orthopair fuzzy set (q-ROFS) to rank the sustainable sources of energy in Haryana, India. The proposed framework includes a novel q-ROFS scoring facility to be used to analyze energy options in uncertain and unclear situations. Moreover, the CRITIC (Criteria Importance Through Inter-Criteria Correlation) is used to identify the objective weights of the evaluation criteria, which is based on the intensity of contrast and discord between the criteria. These objective weights are then added to the subjective expert preferences to reach the final parameters of decision. Hybrid Yager-Power-Weighted Compromise Solution (CoCoSo) approach is then used to undertake the multi-criteria decision-making process and prioritize the energy options that are sustainable. The suggested method has the following benefits: It improves computational stability, maintains the nonlinear weighting effect, it does not have a zero-product problem, and combines both objective and subjective information to provide more credible decision results. The results show that the proposed framework has a solid and useful instrument in helping policymakers to plan sustainably energy and make strategic decisions.

Keywords: q-ROFS; Sustainable-energy; multi-criteria decision-making; CoCoSo; CRITIC; energy-prioritization

1. Introduction

The state of Haryana is a fast-developing state in northern India and has a critical issue on how it can satisfy its increasing energy needs in a sustainable and eco-friendly manner. The growth of state's economy has led to an increase in the demand of energy to drive industry, infrastructure and homes. The demand, however, comes with the need to mitigate the environmental consequences of the existing energy sources, in particular, fossil fuels that pose a threat to the environment with their contribution to air pollution, greenhouse gas emissions, and a lack of natural resources. It is essential to have a sustainable energy future, and the energy requirement of Haryana must be addressed with renewable and cleaner forms of energy that will satisfy the energy requirements and protect the environment in the same breath. This process of decision making is even more hectic when more than one decision is being evaluated with different levels of practicality, economic nature, and sustainability. The variety of variables that must be considered during the selection process could include cost-effectiveness, availability of resources, technical maturity, environmental impact, and its acceptability by society, which is why it is essential to design a framework that could handle such complex and ambiguous data.

Zadeh [1] introduced fuzzy set theory, which has proven useful in addressing the inherent uncertainty frequently encountered in decision-making processes. Moreover, this foundational theory has evolved into more advanced models, such as Atanassov's intuitionistic fuzzy sets (IFS) [2], Atanassov and Gargov's interval-valued intuitionistic fuzzy sets (IVIFS) [3], and Yager's Pythagorean fuzzy sets (PFS) [4], which offer improved adaptability when confronted with imprecise data. A novel extension, the q-rung orthopair fuzzy set (q-ROFS), was introduced by Yager [5], defined by the conditions $0 \leq \beta, \gamma \leq 1, 0 \leq \beta^q + \gamma^q \leq 1, and\ q \geq 1$. When q = 1 and q = 2, respectively, IFS and PFS are specific types of q-ROFS. As q increases, the range of feasible evaluations also expands, making q-ROFS a useful tool for decision-making. However, fuzzy logic and MCDM methods are increasing employed to manage uncertainties in renewable energy source evaluations. The Analytic Hierarchical Process (AHP), VIKOR, and TOPSIS are methods used to prioritize renewable energy options, by considering environmental, economic, and social factors [6–10]. Furthermore, hybrid methodologies that integrate fuzzy techniques with SWARA and the Full Consistency Method (FCM) have been suggested to augment decision precision [11,12]. Contemporary research increasingly emphasizes sophisticated fuzzy models, such as q-ROFS, in conjunction with ranking and weighting methods like CoCoSo and CRITIC, to effectively address intricate decision-making scenarios [13,14]. Studies have also formulated enhanced score and accuracy functions to bolster the dependability of rankings [15–30]. Consequently, the implementation of sustainability policies, environmental finance initiatives, and ESG-focused strategies is becoming increasingly common in the context of long-term energy planning [31,32]. These trends help explain the increasing importance of fuzzy-based multi-criteria decision-making (MCDM) models, particularly q-ROFS, in supporting renewable energy choices when uncertainty is present, thereby promoting sustainable development [33,34]. Advanced decision-making techniques like hybrid q-rung orthopair fuzzy aggregation approaches, objective weighting methods, compromise solution techniques, weighted distance-based approximation algorithms, and entropy-based multicriteria decision-making models have been developed to address complex decision problems and improve decision quality [35–40]. To assess complex data structures and facilitate the best possible decision-making, sophisticated decision-making models under uncertainty have been investigated more in this area by Tyutyunnik and Alguzo [41].

- Despite the availability of various Multi-Criteria Decision-Making (MCDM) and fuzzy logic methods for evaluating renewable energy options, some limitations persist. Moreover, most research focuses on either objective weighting methods or subjective expert evaluations, and doesn't effectively combine both into a single, unified approach. Furthermore, the use of advanced fuzzy models that employ strong ranking methods, such as q-rung orthopair fuzzy sets (q-ROFS), is currently limited in the field of sustainable energy selection, particularly in Haryana. Enhanced scoring techniques are necessary to augment the accuracy and reliability of results amid uncertainty.

This paper proposes a comprehensive framework for decision-making with q-rung orthopair fuzzy sets (q-ROFS). The principal contribution of this study lies in the development of a q-ROFS-based scoring system, which aims to facilitate the management of uncertain and imprecise data. This research enhances the impartiality of the evaluation process by merging subjective expert assessments with the objective weighting approach known as CRITIC. Furthermore, the incorporation of the CoCoSo methodology bolsters ranking stability and mitigates challenges such as the zero-product paradox, thereby ensuring the scoring system's dependability even when confronted with ambiguous or conflicting data. This study offers several important contributions: A comprehensive multi-criteria decision-making framework has been introduced. This framework integrates the q-ROFS, CRITIC, and CoCoSo methods, for evaluating sustainable energy alternatives.

- The research introduces a new tanh-based scoring function under q-ROFS for handling hesitancy through a logarithmic term which better manages uncertainty and improve decision accuracy.
- The proposed framework introduces a hybrid weighting method that combines objective and subjective weights, thereby enhancing the reliability, stability, and consistency of rankings sustainable energy alternatives.
- The application of the proposed framework to Haryana, India, provides valuable insights for policymakers involved in sustainable energy planning. This framework can be applied to other developing region.

The paper is structured as follows: In Section 2 Materials and methods, the CRITIC-driven Hybrid Yager-CoCoSo strategy is described, along with the suggested new scoring function and certain key concepts and definitions. Section 3 Results and discussion, provides sensitivity analysis, comparison analysis, and a case study using the suggested technique in practice. Section 4 wraps up and discusses the main conclusions and possible directions for further research.

2. Materials and methods

2.1. Preliminaries

The nomenclature of the symbols and parameters used throughout this study is provided in Appendix.

Definition 1. Atanassov [2] in a universal set X, an IFS A is defined as

$$A=\{\langle x,\beta(x),\gamma(x)\rangle | x \in X\} \tag{1}$$

Where, $\forall x, \beta(x), \gamma(x) \in [0,1]$, represents membership and non-membership degrees of x to A respectively, such that $0\leq \beta(x)+\gamma(x) \leq 1$ holds, and in turn, the hesitance of x to A is defined as

$$\pi_H=1-\beta(x)\gamma(x) \tag{2}$$

Usually, the pair $\langle \beta, \gamma \rangle$ is called an IFN.

Definition 2. Yager [5] in universal set X, a q-rung orthopair fuzzy set (q-ROFS) A is represented by

$$A=\{\langle x, \beta(x), \gamma(x)\rangle | x \in X\} \tag{3}$$

where, $\beta(x)$ and $\gamma(x)$ represents membership and non-membership degrees of x belonging to the q-ROFS A, such that $\forall x, 0 \leq \beta(x), \gamma(x) \leq 1, 0 \leq \beta(x)^q + \gamma(x)^q \leq 1$ holds, and in turn, the hesitance of x to A is defined as

$$\pi_H = (1 - \beta(x)^q - \gamma(x)^q)^{1/q} \tag{4}$$

where $q > 1$. Usually, the pair $\langle \beta, \gamma \rangle$ is called a q-rung orthopair fuzzy number (q-ROFN).

Definition 3. Liu and Wang [35] let $A=(\beta, \gamma)$ be any q-ROFN, then score function S of A is defined as:

$$S_{liu\ and\ wang}(A) = \beta^q - \gamma^q \tag{5}$$

where $S(A) \in [0, 1]$. Accuracy function H of A is defined as

$$H(A)=\beta^q + \gamma^q \tag{6}$$

Where $H(A) \in [0, 1]$.

Definition 4. Peng et al. [24] let $A=(\beta, \gamma)$ be any q-ROFN, then score function S of A is defined as:

$$S_{peng}(A) = \beta^q - \gamma^q + \left(\frac{e^{\beta^q - \gamma^q}}{e^{\beta^q - \gamma^q + 1}} - \frac{1}{2}\right)\pi^q \tag{7}$$

Where $S(A) \in [-1, 1]$.

Example 1. Given that $a = (0.63,0.63)$ and $b = (0.45,0.45)$, if we employ the score function Liu and Wang [35] to choose the larger q-ROFN, we get:

$$S(a) = S(b) = 0 \tag{8}$$

Therefore, we cannot distinguish between the two q-ROFN, which results in the failure of this score function to rank such alternatives under these types of condition.

Noticing these drawbacks, Liu and Wang [35] proposed the definition of an accuracy function.

$$H(a)=\beta^q + \gamma^q \tag{9}$$

Where $H(a) \in [0, 1]$.

but this also fails under many conditions from which one is if we take $a = (0.5,0.5)$ and $b = (0.7071,0.0)$ for $q = 2$, we get:

$$H(a) = H(b) = 0.5 \tag{10}$$

Additionally, it was discovered that when $\beta = \gamma$, the score function Peng et al. [24] also faced the same situation. To put it another way, Peng et al. [24] will become Liu and Wang [35].

Definition 5. Yap et al. [32] let $Ai = \langle \beta_{i,} \gamma_i \rangle$ $(i = 1,2,\ldots\ldots s)$ be a collection of q-ROFNs, then the aggregated value by the q-ROFYWG operation is a q-ROFN and

$$q-ROFYWA_W(A_1, A_2, \ldots, A_s) = \underset{i=1}{\overset{s}{\oplus}} \left(W_i A^i\right) = \langle \sqrt[q]{min\left(1, \left(\sum_{i=1}^{s} W_i \beta_i^q\right)^{1/\vartheta}\right)}, \sqrt[q]{1 - min\left(1, \left(\sum_{i=1}^{s} W_i (1-\gamma_i^q)^{\vartheta}\right)^{1/\vartheta}\right)} \rangle \tag{11}$$

Where $\vartheta > 0$ and $W = (W1, W2, \ldots. Ws)T$ is the weight vector such that for $W_i > 0, \sum_{i=1}^{s} W_i = 1$.

Definition 6. Akram and Shahzadi [36] let $Ai = \langle \beta_{i,} \gamma_i \rangle$ $(i = 1,2,\ldots\ldots s)$ be a collection of q-ROFNs, then the aggregated value by the q-ROFYWG operation is a q-ROFN and

$$q-ROFYWG_W(A_1, A_2 \ldots., A_s) = \underset{i=1}{\overset{s}{\otimes}} \left(A_i^{W_i}\right) = \langle \sqrt[q]{1 - min\left(1, \left(\sum_{i=1}^{s} W_i (1-\beta_i^q)^{\vartheta}\right)^{1/\vartheta}\right)}, \sqrt[q]{min\left(1, \left(\sum_{i=1}^{s} W_i \gamma_i^q\right)^{1/\vartheta}\right)} \rangle \tag{12}$$

Where $\vartheta > 0$ and $W = (W1, W2, \ldots, Ws)T$ is the weight vector such that for $W_i > 0$, $\sum_{i=1}^{s} W_i = 1$.

2.2. Novel score function

This sub-section presents a new score function and exhibits its comparability and enhancement over some of the current score functions.

2.2.1. New q-rung orthopair fuzzy score function

Definition 7. Let $A = (\beta, \gamma)$ be any q-rung orthopair fuzzy number (q-ROFN). Then, the revised score function S_{new} of A is defined as:

$$S_{new}(A) = tanh(\beta^q - \gamma^q + log\,(0.5 + \pi^q)) \tag{13}$$

Where, $\pi^q = (1 - \beta^q - \gamma^q)^{1/q}$ and $S_{new}(A) \in [-1, 1]$.

Theorem 1. For any q-rungs orthopair fuzzy number $A = (\beta, \gamma)$, where $0 \leq \beta, \gamma \leq 1$ and $q > 1$, the score value $S_{new}(A)$ is bounded in [-1, 1].

Proof. Since $0 \leq \beta^q + \gamma^q \leq 1$, and

$$\pi^q = (1 - \beta^q - \gamma^q)^{1/q} \in [0, 1] \tag{14}$$

It follows:

$$0.5 + \pi^q \in [0.5, 1.5], \Rightarrow log(0.5 + \pi^q) \in [log(0.5), log(1.5)] \approx [-0.693, 0.405] \tag{15}$$

Thus, the argument inside the tanh lies within a bounded interval, and the tanh function maps any real number to (-1,1). Hence,

$$S_{new}(A) \in (-1, 1) \subset [-1,1] \; \square \tag{16}$$

Theorem 2. The score function $S_{new}(A)$ is monotonic increasing in the membership degree β and monotonic decreasing in the non-membership degree γ.

Proof. Let

$$f(\beta,\gamma) = \beta^q - \gamma^q + log\ (0.5 + \pi^q) \tag{17}$$

where $\pi^q = (1 - \beta^q - \gamma^q)^{1/q}$ and $S_{new}(A) = tanh(f)$.

As *tanh(.)* is strictly increasing, it suffices to study the monotonicity of *f.*

1. With respect to β:

$$\frac{\partial f}{\partial \beta} = q\beta^{q-1} - \frac{\beta^{q-1}(1 - \beta^q - \gamma^q)^{\frac{1}{q}-1}}{0.5 + \pi^q} \tag{18}$$

This is generally positive for small to moderate β, showing that *f* increases with β.

2. With respect to γ :

$$\frac{\partial f}{\partial \gamma} = -q\gamma^{q-1} - \frac{\gamma^{q-1}(1-\beta^q-\gamma^q)^{\frac{1}{q}-1}}{0.5+\pi^q}<0 \tag{19}$$

This is show that *f* (and thus S_{new}) decreases with γ.

Therefore, $S_{new}(A)$ is monotonic increasing in β and monotonic decreasing in γ. □

Theorem 3. Let $\alpha = (\beta_1, \gamma_1)$ and $b = (\beta_2, \gamma_2)$ be two *q*-rung orthopair fuzzy numbers. If $\beta_1 > \beta_2$ and $\gamma_1 < \gamma_2$, then

$$S_{new}(a) > S_{new}(b) \tag{20}$$

Proof. According to Theorem 1, the score function S_{new} is monotonically increasing with respect to β and monotonically decreasing with respect to γ. Hence, if $\beta_1 > \beta_2$ and $\gamma_1 < \gamma_2$, the increase in β and the decrease in γ both contribute to an increase in the score value. Therefore,

$$S_{new}(a) > S_{new}(b)\ \square \tag{21}$$

2.2.2. A comparison of existing and new score functions

The next section compares the new and old scoring function. In certain cases, the current scoring function could not lead us to a conclusion, but the new one performed better. This comparison is presented in **Table 1**.

2.3. CRITIC-driven hybrid Yager-COCOSO methodology

2.3.1. Arranging the information in a decision matrix

Let E_1, E_2, …., E_r be alternatives and P_1, P_2, …., P_s be attributes (parameters) with weights ω_1, ω_2, …., ω_s respectively, where $\omega_s \in [0, 1]$ and $\sum_{s=1}^{n} \omega_s = 1$. By using the *q*-ROFNs $\tilde{x}_{rs}$=$\langle\tilde{\beta}_{rs,}\tilde{\gamma}_{rs}\rangle$, the decision maker evaluates the different alternatives E_r with respect to attributes or parameters P_s to construct the decision matrix = $\widehat{D} = (\tilde{x}_{rs})_{m\times n}$, shown as follows:

$$\widehat{D} = \begin{array}{c} E_1 \\ E_2 \\ \vdots \\ E_r \end{array} \begin{pmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \cdots & \tilde{x}_{1s} \\ \tilde{x}_{21} & \tilde{x}_{22} & \because & \tilde{x}_{2s} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{x}_{r1} & \tilde{x}_{r2} & \cdots & \tilde{x}_{rs} \end{pmatrix} \tag{22}$$

Where r = 1,2,….,m and s = 1,2,….,n.

Table 1. Comparison with some existing q-ROF score functions.

Score function	q-rung value	Case 1 a = (0.4,0.1) b = $\sqrt{0.1501, 0.01)}$	Case 2 a = (0.3,0.3) b = (0.5,0.5)
S_{peng} [24]	$q = 1$	a < b	a = b
	$q = 2$	a < b	a = b
	$q = 3$	a > b	a = b
$S_{liu\ and\ wang}$ [35]	$q = 1$	a < b	a = b
	$q = 2$	a = b	a = b
	$q = 3$	a > b	a = b
S_{new}	$q = 1$	a > b	a < b
	$q = 2$	a > b	a < b
	$q = 3$	a < b	a < b

2.3.2. CRITIC-driven hybrid Yager-COCOSO approach

Criteria are recognized as an important source of information while making decisions. Weighting essential criteria can disclose valuable information, often known as "objective weight". Diakoulaki et al. [37] developed the CRITIC (Criteria Importance Through Inter-Criteria Correlation) technique to determine the objective weights of MCDM criteria. The technique yields objective weights that consider both intensity contract and conflict among criteria. The correction coefficient calculates the conflict between criteria based on their intensity contrast and standard deviation. Hussain et al. [40] defines new Yager aggregation operators tailored for q-ROFSs and apply them to solve multi-criteria decision making (MCDM) problems. Yazdani et al. [38] proposes an innovative technique to handle difficult decision-making problems involving several criteria. It combines multiple decision-making techniques to produce a compromise answer that successfully balances competing requirements. The Yager-COCOSO hybrid decision making model is highly beneficial as compared to the traditional one. MCDM resorts to the integration of the nonlinear aggregation power of Yager operators with the trade-off solution of the flexible compromise, the COCOSO method. This integration allows Simultaneous consideration of additive and multiplicative preferences, improving decision robustness. Suppose $\tilde{x}_{rs}$ be the q-ROFN in the decision matrix $\widehat{D} = (\tilde{x}_{rs})_{r\times s}$ then:

Step 1: Normalized Decision Matrix Transform the Decision matrix as showed in Equation (23) into Normalized Decision matrix shown Equation (24).

$$\widehat{D} = (\tilde{x}_{rs})_{r\times s} = \left(\langle\tilde{\beta}_{rs,}\tilde{\gamma}_{rs}\rangle\right)_{m\times n} \tag{23}$$

$$D = (x_{rs})_{m\times n} == \langle\beta_{rs,}\gamma_{rs}\rangle \tag{24}$$

As follows:

$$x_{rs} = \begin{cases} \langle\tilde{\beta}_{rs,}\tilde{\gamma}_{rs}\rangle & : \text{ if } P_s \text{ is a benefit type attribute/paramter} \\ \langle\tilde{\gamma}_{rs}, \tilde{\beta}_{rs}\rangle & : \text{ if } P_s \text{ is a cost type attribute/paramter} \end{cases} \tag{25}$$

Step 2: Compute the score matrix r using the score function.

For each alternative E_r and parameter P_s, compute the score R'_{rs} using the proposed score function in Equation (13).

Step 3: Calculate the standard deviation for each criterion.

The standard deviation σ_s for each parameter P_s is calculated as:

$$\sigma_s = \sqrt{\frac{1}{m}\sum_{r=1}^{m}(R'_{rs} - \bar{R}'_s)^2} \tag{26}$$

Where

- m: Number of alternative.
- R'_{rs}: Standardized score of alternative E_r for parameter P_s.
- $\bar{R}'_s$: Mean of the standardized scores for parameter P_s ,calculated as:

$$\bar{R}'_s = \frac{1}{m}\sum_{r=1}^{m} R'_{rs} \tag{27}$$

Step 4: Calculate the pearson correlation coefficient between parameter.

The Pearson correlation coefficient ρ_{si} qualifies the linear relationship between two parameters P_s and P_i. It is computed using the standardized scores such as:

$$\rho_{si} = \frac{\sum_{r=1}^{m}(R'_{rs}-\bar{R}'_s)(R'_{ri}-\bar{R}'_i)}{\sqrt{\sum_{r=1}^{m}(R'_{rs}-\bar{R}'_s)^2}.\sqrt{\sum_{r=1}^{m}(R'_{ri}-\bar{R}'_i)^2}} \tag{28}$$

Where:

- R'_{rs} and R'_{ri} : Standardized score of alternatives E_r for parameter P_s and P_i respectively.
- $\bar{R}'_s$ and $\bar{R}'_i$: Means of the standardized scores for parameter P_s and P_i respectively.

Step 5: Calculate the information quantity for each parameter.

The information quantity for parameter P_s is calculated as:

$$p_s = \sigma_s \times \left(1 - \sum_{i=1}^{n}\rho_{si}^2\right) \tag{29}$$

Step 6: normalize the information quantity to obtain objective weights.

The objective weight for parameter P_s is determined by normalizing the information quantities:

$$\omega_s = \frac{p_s}{\sum_{s=1}^{n} p_s} \tag{30}$$

Step 7: combine subjective and objective weights.

Assuming subjective weights w_s are provided by experts, the combined weight for criterion C_j is:

$$W_s = \frac{\omega_s \times w_s}{\sum_{s=1}^{n}\omega_s \times w_s} \tag{31}$$

Step 8: Calculate the aggregated value using Yager Weighted Averaging Operator for Each Alternative.

$$YA_r = \langle \sqrt[q]{min\left(1, \left(\sum_{s=1}^{n} W_s \beta_i^q\right)^{1/\vartheta}\right)}, \sqrt[q]{1 - \min\left(1, \left(\sum_{s=1}^{n} W_s \,(1-\gamma_s^q)^{\vartheta}\right)^{1/\vartheta}\right)} \rangle \quad (32)$$

Where $\vartheta > 0$.

Step 9: Calculate the aggregated value using Yager Weighted Geometric Operator for Each Alternative.

$$YG_r = \langle \sqrt[q]{1 - min\left(1, (\sum_{s=1}^{n} W_s (1-\beta_s^q)^{\vartheta})^{1/\vartheta}\right)}, \sqrt[q]{min\left(1, \left(\sum_{s=1}^{n} W_s \gamma_s^q\right)^{1/\vartheta}\right)} \rangle \quad (33)$$

Where $\vartheta > 0$.

Step 10: Compute the Yager Weighted Averaging Score Sm_r and Yager Weighted Geometric Score Pd_r for Each Alternative:

Computing the Yager Weighted Averaging Score Sm_r of Equation (32) and Yager Weighted Geometric Score Pd_r of Equation (33) using the score function Equation (13).

Step 11: Compute the Aggregated Scores K_{ra}, K_{rb} and K_{rc} Calculate the aggregated score using the following formulas:

$$K_{ra} = \frac{Pd_r + Sm_r}{\sum_{r=1}^{m}(Pd_r + Sm_r)} \quad (34)$$

$$K_{rb} = \frac{S_{mr}}{min\,(S_{mr})} + \frac{P_{dr}}{min\,(P_{dr})} \quad (35)$$

$$K_{rc} = \frac{\lambda \times S_{mr} + (1-\lambda) \times Pd_r}{\lambda \times \max(S_{mr} + (1-\lambda) \times \max\,(Pd_r)} \quad (36)$$

Where is the parameter between 0 and 1.

Step 12: Compute the Overall Assessment Value K_r Calculate the overall assessment value for each alternative E_r.

$$K_r = \sqrt[3]{K_{ra} \times K_{rc} \times K_{rc}} + \frac{K_{ra} + K_{rb} + K_{rc}}{3} \quad (37)$$

Step 13: Rank the Alternative Rank the alternatives based on the descending order of K_r. The Alternative with the highest K_r is considered the best choice.

For better clarity and understanding, the complete research procedure is summarized in the methodology flowchart shown below in **Figure 1**.

3. Results and discussion

3.1. Case study: Prioritization of sustainable energy sources in Haryana, India

Haryana, which is in the North of India, is taking laudable steps towards focusing on energy sources that are sustainable to meet the rising demand. energy demand and environmental issues. The state is traditionally dependent on thermal power, but it is shifting to renewable. and renewable energy sources such as solar, biomass and small hydro so that it is energy secure and has less carbon footprint. With the growing industrialization and urbanization, urban energy needs in cities such as Gurugram, Faridabad and Sonipat have rocketed, pointing out the necessity of cleaner options. The energy policies in the State of Haryana such as the Haryana Solar Policy 2016 and Haryana. Energy Conservation Action Plant encourages the use of sustainable energy with such incentives as Renewable Purchase. Rooftop solar systems were obligated (RPOs) and net metered. As illustrated in **Figure 2**, the major renewable energy options in Haryana include solar, biomass, small hydro, and waste-to-energy sources. **Table 2** provides the existing capacity of renewable energy, important initiatives and prospects of renewable energy sources in Haryana whereas **Table 3** provides the future target, planned initiatives, and likely implications of renewable energy sources in Haryana.

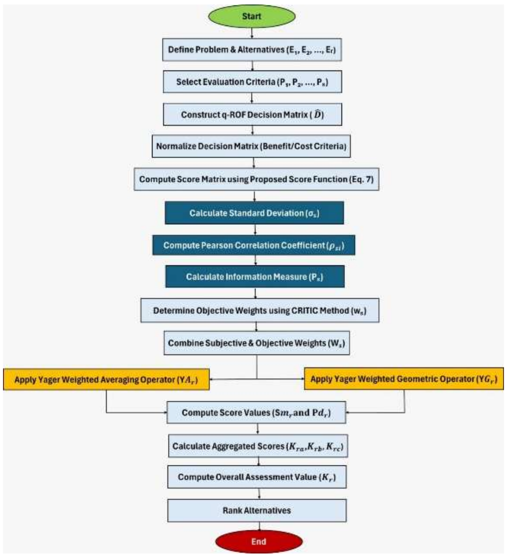

Figure 1. Stepwise flowchart illustrating the CRITIC-driven Yager–COCOSO method under q-ROFS.

Figure 2. Renewable energy option in Haryana.

Table 2. Renewable energy option and their production in Haryana.

Energy source	Current installed capacity (MW)	Key initiatives	Potential (MW)
Solar Energy	1700	Rooftop solar system, Hisar Solar Park, agrivoltaics	4500
Biomass Energy	300	Paddy straw and agricultural residue utilization, co-generation in sugar mills	1400
Small Hydro Power	73	Canal-based hydroelectric projects	100
Waste-to Energy	50	Municipal solid waste plants	150

Table 3. Future aims for renewable energy source.

Energy source	Target capacity by 2030(MW)	Planned initiatives	Expected impact
Solar Energy	4000	Expansion of rooftop solar, utility scale solar parks and agrivoltaics	Meet 10% of the state's energy demand; significant reduction in GHG emissions
Biomass Energy	800	Establishment of additional biomass power plants and cogeneration facilities	Reduction in stubble burning and enhanced rural livelihoods
Small Hydro Power	100	Development of more canal-based hydro projects	Utilization of irrigation infrastructure for clean energy
Waste-to-Energy	150	Expansion of waste-to-energy plants in urban centers to manage municipal solid waste	Reduction in landfill waste and improvement in urban sanitation
Green hydrogen	Pilot Phase	Research and pilot projects in producing green hydrogen for industries and transportation	Explore the future of sustainable fuels, especially for heavy industries and vehicles
Energy Storage	Integrated with Solar Projects	Deployment of battery storage systems for managing renewable energy intermittency	Improve reliability and grid stability with a higher share of renewables.

The renewable energy projects in Haryana have minimized greenhouse gas emissions, alleviated pollution, and enhanced energy. availability in rural communities. The creation of jobs in renewable energy sources, particularly in the has helped in the economic development of the country. biomass supply chain. Haryana has a vision to have a 4GW of renewable energy capacity by 2030 and intends. launch rooftop solar to cover 10 percent of its power requirements. The other emerging technology that the state is investing in is energy. green hydrogen and storage to make it more reliable and efficient.

3.2. Practical implication

Suppose there are four energy alternatives $E = \{E_1, E_{2,} E_3, E_4\}$, where E_1 is Solar Energy, E_2 is Biomass Energy, E_3 is Small Hydro Energy and E_4 is Waste-to-Energy. The evaluation criteria P_j *(j = 1,2,3,4,5,6,7)* are as follows: P_1 represents Resource Availability, P_2 is Cost-Effectiveness, P_3 is Cost-Effectiveness, P_3 is Environmental Impact, P_4 is Land Efficiency, P_5 is Energy Reliability, P_6 is Scalability, and P_7 is Economic Impact. The description of each criterion is briefly stated in **Table 4.**

Table 4. Assessment criteria and their explanations for evaluating sustainable energy alternatives.

Criterion	Description
Resource availability P_1	The energy source must be readily available in the region to be sustainable. In the case of Haryana, the solar and biomass are plentiful. The solar energy, especially the rooftop systems utilize the available sunlight in the area, and the biomass can be obtained using the residue in the farms [42].
Cost-effectiveness P_2	Its energy solution must provide low installation and operation cost to be cost effective. The solar energy has been more cost-competitive particularly as prices of photovoltaic (PV) panels have reduced. Although biomass projects would be higher cost in terms of expenses, they can be cost-effective with time since the resource would be available locally [43].
Environmental impact P_3	The source of energy should be environmentally friendly and less harmful to the environment. The biomass produces are efficient in the reduction of agricultural waste such as stubble burning and solar energy emits no emitted emissions, thus the two are environmentally friendly [42,44].
Land and space efficiency P_4	The solutions must have low land requirements and preferably must be combined with the current infrastructure. Rooftop solar systems are also very space efficient in the sense that they use the existing buildings where no extra land is needed. Biomass can be processed in a land area but can be undertaken at lesser scales [45].
Energy reliability P_5	The energy source must provide stable energy production either on a regular basis or with predictable variations. Combining solar energy with the storage systems will be able to offer consistency of power, and biomass will be able to provide a constant supply of energy even when the weather is unfavorable [44].
Scalability P_6	The energy source should be easy to scale up to suit future needs. Solar energy is flexible because it can be installed in modules, which lets it grow over time. Biomass is similarly scalable, but it may be more site-specific than solar [43].
Economic impact P_7	The energy source should help the local economy and create jobs. Processing agricultural waste and doing other things with biomass might provide a lot of jobs in the area. Solar energy also produces jobs in installation, maintenance, and manufacturing, which helps the local economy [43].

According to the characteristics of the energy alternatives, $P_1, P_4, P_{5,} P_6$ and P_7 are considered benefit criteria, while P_2 and P_3 are cost criteria. By prioritizing sustainable energy sources using these criteria, Haryana can address its environmental challenges while fostering a cleaner and more secure energy future.

Assume the DM has the following subjective weights $w_s = (0.15, 0.2, 0.2, 0.15, 0.1, 0.1, 0.1)$. **Table 5** displays the experts' assessments for alternatives. We applied the proposed method (for q = 3, $\lambda = 0.5$) to choose the best energy source.

Table 5. The q-ROF decision matrix.

	P_1	P_2	P_3	P_4	P_5	P_6	P_7
E_1 (solar energy)	(0.9,0.3)	(0.3,0.7)	(0.8,0.2)	(0.6,0.4)	(0.5,0.4)	(0.8,0.4)	(0.7,0.4)
E_2 (biomass energy)	(0.4,0.7)	(0.6,0.7)	(0.9,0.2)	(0.4,0.6)	(0.4,0.3)	(0.5,0.3)	(0.4,0.4)
E_3(small hydro energy)	(0.5,0.6)	(0.3,0.6)	(0.6,0.6)	(0.5,0.3)	(0.8,0.2)	(0.4,0.6)	(0.7,0.3)
E_4 (waste to energy)	(0.7,0.4)	(0.7,0.2)	(0.8,0.1)	(0.6,0.5)	(0.6,0.3)	(0.5,0.5)	(0.6,0.3)

Step 1: Converting the decision matrix into normalized decision matrix using Equation (24) as:

$$D = \begin{bmatrix} \langle 0.9, 0.3\rangle & \langle 0.7, 0.3\rangle & \langle 0.2, 0.8\rangle & \langle 0.6,0.4\rangle & \langle 0.5,0.4\rangle & \langle 0.8,0.4\rangle & \langle 0.7,0.4\rangle \\ \langle 0.4,0.7\rangle & \langle 0.7,0.6\rangle & \langle 0.2,0.9\rangle & \langle 0.4,0.6\rangle & \langle 0.4,0.3\rangle & \langle 0.5,0.3\rangle & \langle 0.4,0.4\rangle \\ \langle 0.5,0.6\rangle & \langle 0.6,0.3\rangle & \langle 0.6,0.6\rangle & \langle 0.5,0.3\rangle & \langle 0.8,0.2\rangle & \langle 0.4,0.6\rangle & \langle 0.7,0.3\rangle \\ \langle 0.7,0.4\rangle & \langle 0.2,0.7\rangle & \langle 0.1,0.8\rangle & \langle 0.6,0.5\rangle & \langle 0.6,0.3\rangle & \langle 0.5,0.5\rangle & \langle 0.6,0.3\rangle \end{bmatrix} \tag{38}$$

Step 2: Computing the score matrix R for each alternative E_r (r = 1,2,3,4) and parameter P_s (r = 1,2,3,4,5,6,7), using the proposed score function Equation (13) as follows:

$$R = \begin{bmatrix} 0.6749 & 0.5522 & -0.2494 & 0.4509 & 0.3973 & 0.5864 & 0.5167 \\ 0.0138 & 0.3444 & -0.5294 & 0.1708 & 0.4381 & 0.4359 & 0.3586 \\ 0.2203 & 0.4881 & 0.2764 & 0.4359 & 0.6370 & 01798 & 0.5522 \\ 0.5167 & -0.0233 & -0.2532 & 0.3850 & 0.4881 & 0.3298 & 0.4881 \end{bmatrix} \tag{39}$$

Step 3: The standard deviation σ_s for each parameter using Equation (26) is : $\sigma_1 = 0.2961, \sigma_2 = 0.2575, \sigma_3 = 0.3368, \sigma_4 = 0.1253,\ \sigma_5 = 0.1130, \sigma_6 = 0.1715,$ $\sigma_7 = 0.0884$.

Step 4: The pearson correlation coefficient using ρ using Equation (28) is:

$$\rho = \begin{bmatrix} 1.0000 & -0.0538 & 0.0794 & 0.7581 & -0.1828 & 0.4316 & 0.5972 \\ -0.0538 & 1.0000 & 0.2996 & 0.2132 & 0.0277 & 0.2462 & 0.2300 \\ 0.0794 & 0.2996 & 1.0000 & 0.7076 & 0.9240 & -0.7007 & 0.8468 \\ 0.7581 & 0.2132 & 0.7076 & 1.0000 & 0.4562 & -0.1210 & 0.9746 \\ 0.7581 & 0.0277 & 0.9240 & 0.4562 & 1.0000 & -0.9202 & 0.6405 \\ -0.1828 & 0.2462 & -0.7007 & -0.1210 & -0.9202 & 1.0000 & -0.3238 \\ 0.5972 & 0.2300 & 0.8468 & 0.9746 & 0.6405 & -0.3238 & 1.0000 \end{bmatrix} \tag{40}$$

Step 5: The information quantity for parameters is calculated using Equation (29): $p_1 = -0.3436,\quad p_2 = -0.0650,\quad p_3 = -0.8954\ ,\ p_4 = -0.2873, p_5 = -0.2658,$ $p_6 = -0.2923, p_7 = -0.2186$.

Step 6 : The objective weight for each parameter is calculated using Equation (30): $\omega_1 = 0.1451$, $\omega_2 = 0.0275, \omega_3 = 0.3781$, $\omega_4 = 0.1213$, $\omega_5 = 0.1122$, $\omega_6 = 0.1234$, $\omega_7 = 0.0923$.

Step 7: Combine weights for each criteria using Equation (31) are *W1* = 0.1414, *W2* = 0.0357, *W3* = 0.4915, *W4* = 0.1183, *W5* = 0.0729, *W6* = 0.0802, *W7* = 0.0600.

Step 8: Aggregated value using Yager Weighted Averaging Operator Equation (32) for each alternative:

$$\text{Y}\ A_r = \langle 0.6678, 0.5444\rangle\langle 0.4932, 0.6698\rangle\langle 0.6180, 0.4907\rangle\langle 0.4986, 0.6204\rangle \text{ for } \vartheta = 2 \tag{41}$$

Step 9: Aggregated value using Yager Weighted Geometric Operator Equation (33) for each alternative:

$$\text{Y}\ G_r = \langle 0.6679, 0.5443\rangle\langle 0.4933, 0.6697\rangle\langle 0.6181, 0.4906\rangle\langle 0.4987, 0.6203\rangle \text{ for } \vartheta = 2 \tag{42}$$

Step 10: Calculated score value $\mathrm{Sm_r}$ for $Y\,A_r$ are Sm_1 = 0.1835, Sm_2 = 0.1317, Sm_3 = 0.0435, Sm_4 =0.0547.

Calculated score value Pd_r for $Y\,G_r$ are $Pd_1 = 0.18535$, $Pd_2 = 0.1317$, $Pd_3 = 0.0435$, $Pd_4 = 0.0547$

Step 11: Aggregated Scores using Equations (34-36)) are

$$\begin{gathered} K_{1a} = 0.4439, K_{2a} = 0.3186, K_{3a} = 0.1052, K_{4a} = 0.1323 \\ K_{1b} = 8.4401, K_{2b} = 6.0568, K_{3b} = 2.0000, K_{4b} = 2.5158 \\ K_{1c} = 1.0000, K_{2c} = 0.7176, K_{3c} = 0.2370, K_{4c} = 0.2981 \end{gathered} \tag{43}$$

Step 12: The Overall Assessment Value K_r using Equation (37) are

$$K_1 = 4.8479, K_2 = 3.4789, K_3 = 1.1488, K_4 = 1.4450 \tag{44}$$

Step 13: Ranking of all four alternatives are $E_1 \succ E_2 \succ E_4 \succ E_3$.

Thus, the evaluation of renewable energy alternatives yielded the above rankings. This implies that Solar Energy is the most preferred alternative, while small hydro energy plants rank the lowest.

3.3. Comparative analysis

This section provides a comparative look of the proposed CRITIC-driven hybrid Yager–COCOSO method with established decision-making techniques, specifically the q-ROFS-based TOPSIS method [40] and the WDBA method [39], both of which are extensively utilized in multi-criteria decision-making under uncertainty. **Table 6** displays the ranking outcomes derived from both the proposed and existing methodologies. All approaches yield identical rankings, with E_1 (Solar Energy) positioned first and E_3 (Small Hydro Energy) positioned last. This consistency validates and ensures the reliability of the proposed approach. To further quantify this, Spearman rank correlation coefficients of the proposed method with both TOPSIS and WDBA is computed which yields $r = 0.80$. A detailed analysis of **Table 6** shows differences in the rankings of E_2 and E_4.The TOPSIS and WDBA approaches yield differing intermediate rankings, whereas the proposed method offers a more consistent ordering ($E_1 > E_2 > E_4 > E_3$), demonstrating enhanced discrimination among alternatives with similar performance values.

Table 6. Ranking comparison table.

Alternative	Proposed method	(Topsis) [40]	(WDBA) Peng et al. [39]
E_1	1	1	1
E_2	2	3	3
E_3	4	4	4
E_4	3	2	2

The proposed framework agrees with existing methods on the ranking of Solar Energy (E_1) and Small Hydro Energy (E_3) consistently. The difference in rankings of (E_2) and (E_4) reflects the enhanced discriminative capability of the proposed hybrid aggregation, which captures trade-offs that distance-based approaches may not fully account for.

Hybrid Yager-COCOSO Approach clearly yields ranking results that are completely congruent with the current approaches put out by existing decision-making methods. The ranking scores produced by the suggested CRITIC-based hybrid YagerCOCOSO algorithm fully coincide with those produced by the well-known decision-making approaches. Such a powerful correspondence indicates that the suggested framework is powerful and trustworthy. It also demonstrates that it retains the logic of decision-making of established methods and introduces new methods. Along with consistency, the proposed approach has numerous advantages over the prior hybrid integration methods, particularly those that employ product aggregation operators such as the framework suggested by Peng and Huang [14]. In product-based aggregation, an overall aggregated value of zero due to the presence of extremely small or zero-value criterion judgments can reduce the stability of rankings and decrease the ability to differentiate between alternatives.Such behaviour can adversely affect the reliability of decision outcomes, especially in complex and uncertain environments. To address this limitation, the proposed framework employs Yager aggregation operators, which are more flexible and robust in handling extreme or imprecise information. Unlike product-based operators, Yager operators effectively avoid the zero-value collapse problem and ensure smoother aggregation behaviour, resulting in more stable and meaningful ranking results.

3.4. Sensitivity analysis with respect to Yager parameter ϑ

The Yager parameter (ϑ) plays a very critical role in governing the degree of non-linearity which occurs during the aggregation process. To check the influence of this parameter on the final rankings of the alternatives, a sensitivity analysis was performed by varying ϑ across different values, as $\vartheta \in \{1, 2, 4, 6, 8, 10\}$. The parameter q controls the degree of flexibility in the q-rung ortho pair fuzzy environment. Since the given dataset violates the intuitionistic constraint, the case q = 1 is not applicable. Therefore, the sensitivity analysis is conducted for q = 3 keeping same we considered throughout the paper. To analyse its effect, for q = 3 representing a balanced level of fuzziness clearly shown in **Table 7**.

Table 7. Sensitivity analysis w.r.t ϑ (q = 3).

Alternative	$\vartheta = 1$ (Ranking)	$\vartheta = 2$ (Ranking)	$\vartheta = 4$ (Ranking)	$\vartheta = 6$ (Ranking)	$\vartheta = 8$ (Ranking)	$\vartheta = 10$ (Ranking)
E_1	4.8479 (1)	4.0983 (1)	4.0748 (1)	4.3324 (1)	4.5788 (1)	4.8149 (1)
E_2	3.4789 (2)	3.0979 (2)	3.3420 (2)	3.6605 (2)	3.9482 (2)	4.2404 (2)
E_3	1.1488 (4)	1.2216 (4)	1.4182 (4)	1.6045 (4)	1.7210 (4)	1.7931 (4)
E_4	1.4450 (3)	1.7896 (3)	1.9279 (3)	2.0585 (3)	2.1869 (3)	2.3231 (3)

The results indicate that the ranking order of alternatives remains unchanged across all values of ϑ illustrated in **Figure 3** Solar Energy remains at top ranks, followed by Biomass Energy, Waste-to-Energy, and Small Hydro Energy.

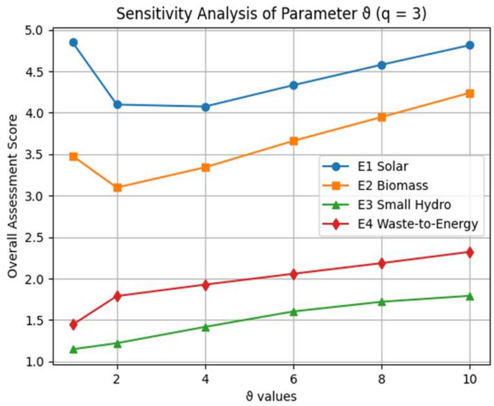

Figure 3. Sensitivity analysis for ϑ (q = 3).

Although the absolute scores increase gradually with higher values of ϑ, the relative ranking structure remains unaffected. Overall, the model represents a controlled sensitivity, capturing variations in decision behaviour without producing inconsistent or random outcomes.

4. Discussion and conclusion

4.1. Discussion

This study proposed a CRITIC-driven Hybrid Yager–COCOSO framework within the q-Rung Orthopair Fuzzy Set (q-ROFS) environment to evaluate and prioritize sustainable energy alternatives for the state of Haryana, India. Incorporating the CRITIC approach along with Yager–COCOSO method helps our model to capture both quantitative knowledge extracted from the variation of data and inter-criteria interaction. The empirical analysis examined the four dominant renewable energy options of solar energy, biomass energy, small hydro energy and waste-to-energy with multiple evaluation criteria to consider including resources availability, cost effectiveness, environmental performance, utility for land space, energy reliability, scalability, economic impact. The ranking outcomes of the suggested framework show that solar energy can be considered as the most desired renewable energy source in Haryana and then comes biomass energy and waste-to-energy, whereas small hydro energy is the lowest among the options that were evaluated. Among the evaluated criteria, Environmental Impact (P_3) was assigned the highest combined weight *W3* = 0.4915, reflecting its dominant influence on the final rankings. Haryana's geography and climatic conditions make solar energy highly sustainable and scalable. Solar Energy performed strongly under this criterion owing to its zero-emission profile, which directly contributed to ranking it on top. Similarly, Biomass Energy benefited from its role in reducing agricultural stubble burning, a pressing environmental concern in Haryana. In contrast, Small Hydro Energy, despite showing relatively strong performance in Energy Reliability (P_5), was cost it by its comparatively weaker environmental scores and limited scalability in the Haryana region, which explains its lowest ranking. Waste-to-energy also portrays average potential because of the growing supply of the municipal solid waste and the fact that it can be used in the provision of integrated waste management and energy recovery systems. Methodologically, the framework suggested has a contribution towards development of multi-criteria decision making (MCDM) methods in the presence of uncertainty. The use of q-ROFS offers a loose framework in the modelling of the hesitation and ambiguity in expert opinions, which cannot be effectively modelled using the classical fuzzy or intuitionistic fuzzy frameworks. Additionally, the proposed nonlinear score function enhances the representation of uncertainty by incorporating hesitation and nonlinear transformation. Furthermore, Yager aggregation operators make aggregation process stronger because in traditional multiplicative aggregation techniques, instability can be experienced when there are very small or zero values, which is not the case with the Yager operators. Comparative analysis with q-ROFS-based TOPSIS and WDBA methods shows consistent ranking results, which foster in validating the reliability and robustness of the proposed framework. Sensitivity analysis further confirms that the model remains stable under variations of Yager parameter ϑ, with consistent ranking patterns observed when changing parameters value. Overall, the proposed framework specifies a reliable, robust and flexible decision-support tool for sustainable energy planning under uncertainty. From a policy implication perspective, the findings of this study carry significant suggestions for Haryana's energy planning. The top ranking of Solar Energy suggests that policymakers should prioritize investments in feasible rooftop solar installations and utility-scale solar system. Biomass Energy, which ranked second, gives an opportunity to simultaneously address agricultural waste management and renewable energy generation for the state. Strategically building Waste-to-Energy plants in urban centers where municipal solid waste supply is steady. Small Hydro Energy may be considered only for specific micro-hydro applications in areas with sufficient water sources availability.

4.2. Conclusion

The paper proposes a hybrid multi-criteria decision-making model, which is founded on the mixture of CRITIC weighting and the Yager-COCOSO ranking method in the context of q-Rung Orthopair Fuzzy Set. The proposed model will be used to facilitate evaluation and prioritization of renewable energy alternatives when there are uncertainty and incomplete information. Empirical analysis shows that solar energy has the topmost priority in sustainable energy development in Haryana followed by biomass energy and waste-to-energy technologies. Small hydro energy on the other hand has relatively low potential because of geographical limitations in the region. These results underline the necessity to pay attention to renewable energy sources that will correspond to local environmental and resource factors. The suggested decision-making framework is a systematic and transparent instrument of sustainable energy evaluation, and it can help policymakers and planners develop effective policies to resort to renewable energy. The framework enhances the accuracy of the decisions made within a complex evaluation setting because it includes fuzzy modeling and objective weighting methods. Further studies can expand the level of this framework to involve more renewable energy technologies and the incorporation of dynamic evaluation standards that are responsive to changing technological, economic and policy environments.

Despite the contributions of this study, certain limitations we should also acknowledge. The analysis is confined to only four renewable energy alternatives, and future studies may extend the framework to include additional options such as wind energy and geothermal power in accordance with the region. Additionally, the expert-assigned subjective weights inherently carry a degree of subjectivity, and variations in expert opinion may influence the final rankings. The study is also region-specific to Haryana, and the applicability of these findings to other geographical and emerging economies contexts for further investigation. Furthermore, the use of more sophisticated types of fuzzy extensions and comparative analysis with other methods of decision-making could also help to increase the relevance and strength of the suggested strategy.

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Appendix

Table A1. Nomenclature.

Symbol	**Description**
β, γ	Membership and non-membership degrees
π_H	Hesitancy degree
q	Rung parameter
A_i	i-th alternative
P_s	s-th criterion
$\widehat{D} = (\tilde{x}_{rs})_{m\times n}$	Decision matrix with q-rung orthopair fuzzy number corresponding to alternative E_r under attribute P_s
w_s	Subjective weight (assigned by experts)
ω_s	Objective weight (computed using CRITIC method)
W_s	Final combined weight (integration of ω_s *and* w_s)
σ_s	Standard deviation of criterion
ρ_{si}	Correlation coefficient
p_s	Information quantity
$S_{new}(A)$	Proposed score function
K_r	Overall assessment value
λ	CoCoSo balance parameter
$S_{\text{liu and wang}}(A)/\ S_{\text{peng}}(A)$	Existing score function
$\mathrm{Y}A_r$	Yager weighted averaging aggregation
$\mathrm{Y}G_r$	Yager weighted geometric aggregation
ϑ	Yager balance parameter
Sm_r	Score of WA aggregation
Pd_r	Score of WG aggregation