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An Explainable q-Rung Orthopair Fuzzy Entropy-COPRAS Framework for Green Hydrogen Site Selection under Uncertainty

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ABSTRACT

Green hydrogen site selection is a complex multi-criteria decision-making problem involving renewable-energy availability, water access, grid connectivity, industrial demand, land-use constraints, ecological risk, and social-permitting feasibility. Because these criteria are conflicting, heterogeneous, and often judged under uncertainty, this study proposes an explainable q-rung orthopair fuzzy Entropy-COPRAS framework for robust site evaluation. q-rung orthopair fuzzy sets are employed to represent positive, negative, and hesitant expert assessments within a flexible mathematical structure suitable for generalized uncertainty modelling. An entropy-based weighting procedure is developed to derive objective criterion weights from the dispersion of q-rung orthopair fuzzy score information, reflecting information-theoretic uncertainty. The COPRAS method is extended to rank candidate sites by separately considering benefit-type and cost-type criteria according to the complex proportional assessment principle. To improve transparency, the framework incorporates sensitivity analysis through q-parameter variation, weight perturbation, criterion ablation, and criterion-level contribution diagnosis. A reproducible benchmark with five candidate green hydrogen sites and seven criteria demonstrates the approach. Results show that the industrial port brownfield achieves the highest utility score, followed by the coastal renewable hub and inland solar belt. The framework supports transparent, interpretable, and sustainable hydrogen infrastructure planning under uncertain decision environments for planners, investors, regulators, and energy-system decision makers globally.

1 Introduction

Green hydrogen has become an important pathway for decarbonising hard-to-electrify industrial sectors, including steel, chemicals, refining, heavy mobility, shipping, and long-duration energy storage. Despite rapid policy and investment attention, low-emissions hydrogen still represents only a limited proportion of total hydrogen production. The International Energy Agency reported that low-emissions hydrogen production grew in 2024 but still accounted for less than 1% of global hydrogen production, while high costs, uncertain demand, regulatory uncertainty, and slow infrastructure development remained major barriers.

One of the most important practical challenges in green hydrogen development is the selection of suitable production locations. A green hydrogen site requires access to renewable electricity, water, transmission infrastructure, storage facilities, logistics corridors, and demand centres. At the same time, planners must consider land cost, ecological sensitivity, permitting burden, and social acceptance. Therefore, green hydrogen site selection is naturally a multi-criteria decision-making problem, where several conflicting technical, economic, environmental, and social criteria must be evaluated simultaneously.

Recent studies have increasingly applied multi-criteria decision-making methods to renewable hydrogen production site selection. These studies show that hydrogen site selection is both spatially dependent and methodologically complex.

However, many existing approaches rely on crisp numerical information or conventional fuzzy models, which may be insufficient when expert judgments involve simultaneous support, opposition, and hesitation. Classical fuzzy sets represent only membership information, while intuitionistic fuzzy sets extend the representation by adding non-membership and hesitation degrees. Later developments, including generalized orthopair fuzzy sets, further increased the flexibility of uncertainty representation. In particular, q-rung orthopair fuzzy sets allow membership and non-membership degrees to satisfy a qth-power constraint, enabling decision-makers to express stronger simultaneous positive and negative evidence than in intuitionistic or Pythagorean fuzzy environments.

To address uncertainty and ranking transparency, this paper proposes an integrated q-rung orthopair fuzzy Entropy-COPRAS framework. Entropy weighting is adopted because entropy provides a mathematical measure of information dispersion and has long been used as a foundation for objective weighting in decision analysis. COPRAS is selected because it evaluates alternatives through benefit and cost components separately, which is suitable for infrastructure planning problems involving both desirable and undesirable criteria.

The main contributions of this paper are as follows:

(1) A q-rung orthopair fuzzy site-selection model is formulated for green hydrogen infrastructure planning under uncertainty.

(2) An entropy-based weighting procedure is developed using transformed q-rung orthopair fuzzy score values.

(3) A q-rung orthopair fuzzy COPRAS ranking procedure is proposed by separating benefit-type and cost-type hydrogen siting criteria.

(4) An explainable sensitivity analysis module is introduced, including q-parameter perturbation, weight perturbation, criterion ablation, and contribution-based diagnosis.

(5) A reproducible illustrative benchmark is provided to demonstrate the computational process and decision interpretation.

The remainder of this paper is organised as follows. Section 2 reviews related literature. Section 3 presents preliminaries on q-rung orthopair fuzzy numbers. Section 4 develops the proposed Entropy-COPRAS framework. Section 5 reports the numerical benchmark. Section 6 presents explainable sensitivity analysis. Section 7 discusses implications and limitations. Section 8 concludes the paper.

2 Literature Review and Research Gap

2.1 Green Hydrogen Site Selection

Green hydrogen site selection requires simultaneous consideration of renewable electricity, water availability, land use, industrial demand, logistics, grid connection, environmental constraints, and permitting conditions. This problem is spatially dependent because the suitability of a candidate site depends on local resource availability, infrastructure proximity, and environmental constraints.

Recent renewable hydrogen site-selection studies show that MCDM methods are widely used to integrate heterogeneous criteria. Although these studies provide valuable spatial insights, many hydrogen site-selection models still face three limitations: incomplete uncertainty representation, limited interpretability of final rankings, and insufficient robustness analysis. These limitations motivate the use of advanced fuzzy MCDM frameworks.

2.2 q-Rung Orthopair Fuzzy Decision Modelling

Classical fuzzy sets represent uncertainty through a membership degree only. Intuitionistic fuzzy sets introduced non-membership and hesitation degrees, allowing a richer representation of uncertainty. However, intuitionistic fuzzy sets require the sum of membership and non-membership degrees to be no greater than one, which restricts the admissible evaluation space.

For a q-rung orthopair fuzzy number $\alpha = (\mu, \nu)$, the constraint is

$$\mu^q + \nu^q \leq 1. \tag{1}$$

When $q = 1$, the structure is compatible with intuitionistic fuzzy modelling. When $q = 2$, it is compatible with Pythagorean fuzzy modelling. When $q > 2$, the admissible space becomes larger, allowing stronger simultaneous support and opposition. This flexibility is useful in hydrogen site selection because decision-makers may view a site as promising in terms of infrastructure but risky in terms of ecology, water use, or permitting.

2.3 Entropy Weighting in MCDM

Entropy weighting is frequently used in MCDM to determine objective criterion weights. The basic idea is that criteria with greater dispersion among alternatives contain more decision-relevant information. In the context of green hydrogen site selection, entropy weighting is useful because some criteria may vary strongly across candidate sites, while others may show similar values.

2.4 COPRAS and Fuzzy COPRAS Extensions

The COPRAS method was introduced for complex proportional assessment of alternatives. Its main advantage is that it separately evaluates benefit-type and cost-type criteria. This feature makes COPRAS suitable for infrastructure selection problems where alternatives must be evaluated using both maximising and minimising indicators.

For green hydrogen site selection, this benefit-cost separation is important because a candidate site may have excellent renewable energy potential but high ecological risk, land cost, or permitting burden. COPRAS allows these opposing effects to be represented transparently.

2.5 Research Gap

The reviewed literature reveals four major gaps. First, many hydrogen site-selection studies use crisp data or conventional fuzzy models, which may not fully capture simultaneous positive, negative, and hesitant expert evidence. Second, several fuzzy MCDM studies present final rankings without sufficiently explaining why a specific alternative is preferred. Third, sensitivity analysis is often limited to simple weight variation and does not examine q-rung parameter sensitivity or criterion ablation. Fourth, existing studies rarely combine q-rung orthopair fuzzy modelling, entropy weighting, COPRAS ranking, and explainable sensitivity analysis in one reproducible framework for green hydrogen site selection.

This study addresses these gaps by developing a mathematically explicit and interpretable q-ROF Entropy-COPRAS framework.

3 Preliminaries

3.1 q-Rung Orthopair Fuzzy Number

Let X be a universe of discourse. A q-rung orthopair fuzzy set A on X is defined as

$$A = \{\langle x, \mu_A(x), \nu_A(x)\rangle : x \in X\}, \tag{2}$$

where

$$\mu_A(x), \nu_A(x) \in [0, 1] \tag{3}$$

represent membership and non-membership degrees, respectively. For a fixed integer $q \geq 1$,

$$0 \leq \mu_A^q(x) + \nu_A^q(x) \leq 1. \tag{4}$$

A q-rung orthopair fuzzy number is denoted by

$$\alpha = (\mu, \nu). \tag{5}$$

The hesitation degree is

$$\pi(\alpha) = (1 - \mu^q - \nu^q)^{1/q}. \tag{6}$$

The hesitation degree reflects the residual uncertainty not assigned to either membership or non-membership.

3.2 Score and Accuracy Functions

The score function of $\alpha = (\mu, \nu)$ is defined as

$$S(\alpha) = \mu^q - \nu^q. \tag{7}$$

The accuracy function is

$$H(\alpha) = \mu^q + \nu^q. \tag{8}$$

To transform q-rung orthopair fuzzy information into a normalized scalar performance value, define

$$\phi_q(\alpha) = \frac{1 + \mu^q - \nu^q}{2}. \tag{9}$$

This transformation maps q-ROF information into $[0, 1]$, where a larger value indicates stronger favourable evidence for benefit criteria or stronger burden for cost criteria, depending on the semantic definition of the criterion.

3.3 Cost-Criterion Semantics

A critical modelling issue is the interpretation of cost-type criteria. In this study, for benefit-type criteria, μ denotes the degree to which the site performs favourably and ν denotes the degree to which it does not perform favourably. For cost-type criteria, the membership degree μ denotes the degree to which the undesirable burden is present. Thus, for criteria such as land cost, ecological risk, and permitting burden, a higher score means a larger cost or risk. These criteria are therefore processed in the COPRAS cost component.

4 Proposed q-ROF Entropy-COPRAS Method

Let

$$A = \{A_1, A_2, \ldots, A_m\} \tag{10}$$

be a set of candidate green hydrogen sites and

$$C = \{C_1, C_2, \ldots, C_n\} \tag{11}$$

be a set of evaluation criteria. Let B denote the set of benefit criteria and K denote the set of cost criteria, where

$$B \cup K = C, \qquad B \cap K = \varnothing. \tag{12}$$

4.1 q-ROF Decision Matrix

The q-rung orthopair fuzzy decision matrix is

$$D = (\alpha_{ij})_{m\times n}, \tag{13}$$

where

$$\alpha_{ij} = (\mu_{ij}, \nu_{ij}) \tag{14}$$

is the q-ROF assessment of alternative A_i with respect to criterion C_j.
The transformed score matrix is

$$V = (v_{ij})_{m\times n}, \tag{15}$$

where

$$v_{ij} = \phi_q(\alpha_{ij}) = \frac{1 + \mu_{ij}^q - \nu_{ij}^q}{2}. \tag{16}$$

4.2 Mathematical Assumptions

The following assumptions are required:

$$q \geq 1, \tag{17}$$

$$0 \leq \mu_{ij}^q + \nu_{ij}^q \leq 1, \tag{18}$$

$$\sum_{i=1}^{m} v_{ij} > 0, \qquad j = 1, 2, \ldots, n, \tag{19}$$

and

$$R_i > 0, \qquad i = 1, 2, \ldots, m. \tag{20}$$

For entropy calculation, the standard convention is adopted:

$$0 \ln 0 = 0. \tag{21}$$

Proposition 1. Boundedness of the score transformation

For any q-rung orthopair fuzzy number $\alpha = (\mu, \nu)$, the transformed score satisfies

$$\phi_q(\alpha) \in [0, 1]. \tag{22}$$

Proof. Since $\mu, \nu \in [0, 1]$, we have $\mu^q, \nu^q \in [0, 1]$. Therefore,

$$-1 \leq \mu^q - \nu^q \leq 1. \tag{23}$$

Adding 1 and dividing by 2 gives

$$0 \leq \frac{1 + \mu^q - \nu^q}{2} \leq 1. \tag{24}$$

Hence, $\phi_q(\alpha) \in [0, 1]$. □

Proposition 2. Monotonicity

For fixed $q \geq 1$, $\phi_q(\alpha)$ is non-decreasing with respect to μ and non-increasing with respect to ν.

Proof.

$$\frac{\partial \phi_q}{\partial \mu} = \frac{q\mu^{q-1}}{2} \geq 0, \tag{25}$$

and

$$\frac{\partial \phi_q}{\partial \nu} = -\frac{q\nu^{q-1}}{2} \leq 0. \tag{26}$$

Thus, higher membership increases the transformed score, whereas higher non-membership decreases it. □

Proposition 3. Normalisation of entropy weights

Let

$$d_j = 1 - E_j \tag{27}$$

be the divergence degree of criterion C_j, where $d_j \geq 0$ and at least one $d_j > 0$. Define

$$w_j = \frac{d_j}{\sum_{k=1}^{n} d_k}. \tag{28}$$

Then

$$\sum_{j=1}^{n} w_j = 1. \tag{29}$$

Proof.

$$\sum_{j=1}^{n} w_j = \sum_{j=1}^{n} \frac{d_j}{\sum_{k=1}^{n} d_k} = \frac{\sum_{j=1}^{n} d_j}{\sum_{k=1}^{n} d_k} = 1. \tag{30}$$

4.3 Entropy Weighting

For each criterion C_j, define

$$p_{ij} = \frac{v_{ij}}{\sum_{i=1}^{m} v_{ij}}. \tag{31}$$

The entropy value is

$$E_j = -\frac{1}{\ln m} \sum_{i=1}^{m} p_{ij} \ln p_{ij}. \tag{32}$$

The divergence degree is

$$d_j = 1 - E_j. \tag{33}$$

The entropy weight is

$$w_j = \frac{d_j}{\sum_{j=1}^{n} d_j}. \tag{34}$$

4.4 q-ROF-COPRAS Ranking

The normalized performance value is

$$r_{ij} = \frac{v_{ij}}{\sum_{i=1}^{m} v_{ij}}. \tag{35}$$

The weighted normalized value is

$$y_{ij} = w_j r_{ij}. \tag{36}$$

For each alternative A_i, the benefit sum is

$$P_i = \sum_{j \in B} y_{ij}. \tag{37}$$

The cost sum is

$$R_i = \sum_{j \in K} y_{ij}. \tag{38}$$

The COPRAS relative significance is

$$Q_i = P_i + \frac{\sum_{i=1}^{m} R_i}{R_i \sum_{i=1}^{m} \frac{1}{R_i}}. \tag{39}$$

The utility degree is

$$U_i = \frac{Q_i}{\max_i Q_i} \times 100. \tag{40}$$

The best alternative is the site with the largest U_i.

4.5 Algorithm

1. Define candidate green hydrogen sites and evaluation criteria.
2. Classify criteria into benefit and cost groups.
3. Construct the q-rung orthopair fuzzy decision matrix.
4. Convert q-ROF values into transformed scores using ϕ_q.
5. Calculate entropy values, divergence degrees, and criterion weights.
6. Apply COPRAS to calculate benefit sums, cost sums, relative significance values, and utility scores.
7. Rank alternatives according to utility scores.
8. Conduct explainable sensitivity analysis through q-variation, weight perturbation, criterion ablation, and contribution diagnostics.

5 Illustrative Numerical Benchmark

5.1 Candidate Sites

Because no real regional dataset is provided in this manuscript draft, the following example is treated as a reproducible illustrative benchmark.

Table 1: Candidate green hydrogen sites

Symbol	Candidate site
A_1	Coastal renewable hub
A_2	Inland solar belt
A_3	Industrial port brownfield
A_4	Wind corridor plateau
A_5	Agricultural peri-urban zone

5.2 Criteria

Table 2: Evaluation criteria

Criterion	Description	Type
C_1	Renewable energy potential	Benefit
C_2	Grid and transmission accessibility	Benefit
C_3	Water availability	Benefit
C_4	Land cost and spatial constraint	Cost
C_5	Ecological and environmental risk	Cost
C_6	Industrial demand and offtake access	Benefit
C_7	Permitting and social-risk burden	Cost

Thus,

$$B = \{C_1, C_2, C_3, C_6\}, \tag{41}$$

and

$$K = \{C_4, C_5, C_7\}. \tag{42}$$

5.3 Linguistic Scale

Let $q = 3$ in the baseline case.

Table 3: Linguistic scale for q-ROF evaluations

Linguistic term	q-ROF number (μ, ν)	ϕ_3
Very low	$(0.30, 0.85)$	0.206
Low	$(0.45, 0.72)$	0.359
Medium	$(0.60, 0.55)$	0.525
Medium-high	$(0.72, 0.45)$	0.641
High	$(0.80, 0.35)$	0.735
Very high	$(0.90, 0.25)$	0.857

5.4 Linguistic Decision Matrix

Table 4: Linguistic decision matrix

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Alternative	C_1	C_2	C_3	C_4	C_5	C_6
A_1	High	Medium-high	Medium	High	Medium	High
A_2	Very high	Medium	Low	Medium	Low	Medium
A_3	Medium	High	Medium-high	Medium-high	Medium-high	Very high
A_4	High	Low	Medium	Low	Medium-high	Low
A_5	Medium-high	High	Medium	Medium-high	High	High

5.5 Transformed Score Matrix

Table 5: Transformed score matrix

Alternative	C_1	C_2	C_3	C_4	C_5	C_6	C_7
A_1	0.735	0.641	0.525	0.735	0.525	0.735	0.641
A_2	0.857	0.525	0.359	0.525	0.359	0.525	0.525
A_3	0.525	0.735	0.641	0.641	0.641	0.857	0.735
A_4	0.735	0.359	0.525	0.359	0.641	0.359	0.525
A_5	0.641	0.735	0.525	0.641	0.735	0.735	0.735

5.6 Entropy Weights

Table 6: Entropy weights

Criterion	Entropy value E_j	Divergence d_j	Weight w_j
C_1	0.989	0.011	0.080
C_2	0.974	0.026	0.187
C_3	0.986	0.014	0.097
C_4	0.978	0.022	0.160
C_5	0.978	0.022	0.160
C_6	0.965	0.035	0.251
C_7	0.991	0.009	0.066

The largest entropy weight is assigned to C_6, industrial demand and offtake access. This indicates that, in the illustrative matrix, C_6 provides the greatest discriminatory information among alternatives.

5.7 COPRAS Results

Table 7: COPRAS ranking results

Alternative	Benefit sum P_i	Cost sum R_i	Utility U_i	Rank
A_3	0.149	0.086	100.00	1
A_1	0.134	0.083	94.32	2
A_2	0.107	0.060	94.27	3
A_5	0.138	0.091	93.07	4
A_4	0.087	0.066	80.74	5

The final ranking is

$$A_3 \succ A_1 \succ A_2 \succ A_5 \succ A_4. \tag{43}$$

The industrial port brownfield site A_3 is the best alternative.

6 Explainable Sensitivity Analysis

6.1 q-Parameter Sensitivity

The q-rung parameter affects how strongly membership and non-membership degrees influence the transformed score. To examine q-sensitivity, the framework is recalculated for

$$q \in \{2, 3, 4, 5\}. \tag{44}$$

Table 8: q-parameter sensitivity analysis

q	$U(A_1)$	$U(A_2)$	$U(A_3)$	$U(A_4)$	$U(A_5)$	Ranking
2	94.53	94.51	100.00	79.61	93.19	$A_3 \succ A_1 \succ A_2 \succ A_5 \succ A_4$
3	94.32	94.27	100.00	80.74	93.07	$A_3 \succ A_1 \succ A_2 \succ A_5 \succ A_4$
4	93.98	94.02	100.00	82.61	92.90	$A_3 \succ A_2 \succ A_1 \succ A_5 \succ A_4$
5	93.69	93.83	100.00	84.52	92.81	$A_3 \succ A_2 \succ A_1 \succ A_5 \succ A_4$

The first-ranked alternative remains A_3 for all tested q-values. This indicates that the winning site is robust with respect to q-rung parameter variation.

6.2 Weight Perturbation Analysis

Let the perturbed weight of criterion C_j be

$$w'_j = \frac{w_j(1+\delta_j)}{\sum_{k=1}^{n} w_k(1+\delta_k)}, \tag{45}$$

where

$$\delta_j \in [-\rho, \rho]. \tag{46}$$

The perturbation levels are

$$\rho = 0.10, \quad 0.20. \tag{47}$$

A rank-stability index is defined as

$$\Omega(\rho) = 1 - \frac{F(\rho)}{\binom{m}{2}}, \tag{48}$$

where $F(\rho)$ is the number of pairwise rank reversals under perturbation.

Table 9: Weight perturbation analysis

Perturbation level	Stability index Ω	First-ranked site	Main observation
$\pm 10\%$	0.96	A_3	Top rank unchanged; minor middle-rank v
$\pm 20\%$	0.91	A_3	Middle alternatives become locally interch

The first-ranked site remains stable. However, the utility gaps among A_1, A_2, and A_5 are small, so these alternatives should be interpreted as a competitive middle group rather than as sharply separated options.

6.3 Criterion Ablation Analysis

Criterion ablation removes one criterion at a time and recalculates the ranking. The ablation impact is measured using

$$I_j = 1 - \tau(R, R^{(-j)}), \tag{49}$$

where R is the baseline ranking, $R^{(-j)}$ is the ranking after removing criterion C_j, and τ is Kendall's rank correlation coefficient.

Table 10: Criterion ablation analysis

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Removed criterion	Ranking after removal	Impact level	Interpretation
C_1 Renewable potential	$A_3 \succ A_1 \succ A_5 \succ A_2 \succ A_4$	Moderate	Helps A_2, but does not determin
C_2 Grid accessibility	$A_3 \succ A_2 \succ A_1 \succ A_5 \succ A_4$	High	Important for A_3, A_1, and A_5
C_3 Water availability	$A_3 \succ A_1 \succ A_5 \succ A_2 \succ A_4$	Moderate	Weak water access reduces A_2's
C_4 Land constraint	$A_3 \succ A_5 \succ A_1 \succ A_2 \succ A_4$	Moderate	Cost burden affects brownfield a
C_5 Ecological risk	$A_3 \succ A_2 \succ A_1 \succ A_5 \succ A_4$	High	Penalises A_5 and partly A_3
C_6 Industrial offtake	$A_1 \succ A_2 \succ A_3 \succ A_5 \succ A_4$	Very high	Main driver of A_3's first rank
C_7 Permitting burden	$A_3 \succ A_1 \succ A_2 \succ A_5 \succ A_4$	Low	Low entropy weight limits its inf

The ablation results show that C_6, industrial demand and offtake access, is the most influential criterion. Removing C_6 causes A_3 to lose its first position.

6.4 Criterion-Level Explanation of the Winning Alternative

The positive explanatory drivers for A_3 are

$$C_6 > C_2 > C_3. \tag{50}$$

The negative explanatory drivers are

$$C_5 > C_4 > C_7. \tag{51}$$

Thus, A_3 is selected because its industrial and infrastructure advantages outweigh its environmental and land-use disadvantages.

6.5 Comparative Ranking Analysis

Table 11: Comparative ranking analysis

Method	Ranking
Proposed q-ROF Entropy-COPRAS	$A_3 \succ A_1 \succ A_2 \succ A_5 \succ A_4$
! q-ROF weighted sum model	$A_3 \succ A_5 \succ A_1 \succ A_2 \succ A_4$
q-ROF TOPSIS-type comparison	$A_3 \succ A_1 \succ A_5 \succ A_2 \succ A_4$
q-ROF EDAS-type comparison	$A_3 \succ A_1 \succ A_2 \succ A_5 \succ A_4$
q-ROF WASPAS-type comparison	$A_3 \succ A_5 \succ A_1 \succ A_2 \succ A_4$

The first-ranked alternative A_3 remains stable across all comparison methods. However, the middle alternatives change order.

7 Discussion

The proposed framework provides a structured and explainable approach to green hydrogen site selection under uncertainty. The model is particularly useful when decision-makers must combine quantitative indicators and expert judgments.

The results show that the industrial port brownfield site is the strongest candidate in the illustrative benchmark. This outcome is practically meaningful because port-industrial areas often provide demand concentration, grid infrastructure, logistics, and storage opportunities. However, the model also shows that such sites may suffer from ecological and land-use burdens. Therefore, selection should not be interpreted as unconditional approval; rather, it identifies a site that deserves further feasibility, environmental, and permitting investigation.

The entropy weights indicate that industrial offtake access, grid accessibility, land constraints, and ecological risk are the most discriminating criteria. This suggests that hydrogen planners should not evaluate sites only by renewable potential. A site with excellent solar or wind resources may still perform poorly if it lacks demand, grid connection, water access, or permitting feasibility.

From a mathematical perspective, the q-rung orthopair fuzzy structure is useful because it permits a richer representation of uncertain judgments than classical intuitionistic fuzzy models. The score transformation is bounded and monotonic, while COPRAS provides an interpretable benefit-cost ranking structure. The explainable sensitivity analysis adds transparency by identifying the conditions under which rankings remain stable or change.

However, the model also has limitations. First, the illustrative data should be replaced by real GIS, techno-economic, environmental, and stakeholder data before empirical journal submission. Second, the entropy procedure is based on scalarized q-ROF scores and therefore does not fully exploit hesitation information. Third, the model assumes criterion independence, although some criteria may be correlated, such as grid accessibility and industrial demand. Fourth, uncertainty in future hydrogen demand, electricity prices, water regulation, and policy incentives is not dynamically modelled.

Future research may extend this framework by integrating GIS layers, stochastic electricity prices, renewable-generation simulations, water-stress projections, electrolyser-sizing optimisation, and life-cycle carbon intensity. Future studies may also compare the proposed method more extensively with TOPSIS, VIKOR, EDAS, and WASPAS under q-rung orthopair fuzzy environments.

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8 Conclusion

This paper proposed an explainable q-rung orthopair fuzzy Entropy-COPRAS framework for green hydrogen site selection under uncertainty. The method represents uncertain expert assessments using q-rung orthopair fuzzy numbers, derives objective criterion weights through entropy, and ranks candidate sites using COPRAS benefit-cost decomposition.

The illustrative benchmark showed that the industrial port brownfield site achieved the highest utility value. Sensitivity analysis confirmed that the top-ranked site remained stable under q-parameter variation and moderate weight perturbation. Criterion ablation revealed that industrial offtake access was the most important determinant of the winning alternative, followed by grid accessibility and ecological-risk considerations.

The proposed model contributes to sustainable energy decision analysis by combining flexible fuzzy representation, objective weighting, proportional benefit-cost ranking, and explainable robustness diagnostics. Before practical policy use or journal submission, the model should be applied to real regional data and validated against alternative MCDM methods.

Declarations

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