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A Hybrid AHP–Evidential Reasoning Framework for Multi-Criteria Assessment of Wind-Based Green Hydrogen Production Scenarios on the Northern Coast of Mauritania

Mohamed Hamoud [1,*], Eduardo Blanco-Davis [1,*], Ana Armada Bras [2], Sean Loughney [1], Musa Bashir [3], Varha Maaloum [4,5], Ahmed Mohamed Yahya [4,5] and Jin Wang [1]

1 Liverpool Logistics, Offshore and Marine (LOOM) Research Institute, Liverpool John Moores University, Liverpool L3 3AF, UK
2 Built Environment and Sustainable Technologies (BEST) Research Institute, Liverpool John Moores University, Liverpool L3 3AF, UK
3 Department of Civil and Environmental Engineering, University of Liverpool, Liverpool L69 7ZX, UK
4 Applied Research Unit for Renewable Energies in Water and Environment (URA3E), University of Nouakchott, Nouakchott BP 880, Mauritania
5 Mauritanian Society of Renewable Energies and Green Hydrogen (2SMERHV), Nouakchott, Mauritania
* Correspondence: m.hamoud2022@ljmu.ac.uk (M.H.); e.e.blancodavis@ljmu.ac.uk (E.B.-D.)

Abstract

The northern coast of Mauritania presents a strategic opportunity for clean energy investment due to its remarkable potential for green hydrogen production through wind energy. To determine the best location for wind-based green hydrogen production, this paper established a Multi-Criteria Decision-Making framework (MCDM) that combines the Analytic Hierarchy Process (AHP) and Evidential Reasoning (ER) to assess five coastal sites: Nouakchott, Nouamghar, Tasiast, Boulanoir, and Nouadhibou. Four main criteria (i.e., economic, technical, environmental, and social) and twelve sub-criteria were taken into account in the assessment. To ensure reliability and contextual accuracy, the data used in this study were obtained from geographic databases, peer-reviewed literature, and structured expert questionnaires. The results indicate that site 5 (Nouadhibou) is the most suitable location for green hydrogen generation using wind energy. Sensitivity analysis confirms the robustness of the ranking results, validating the reliability of the proposed hybrid framework. The findings of this study provide critical, data-driven decision-support insights for investors and policymakers, guiding the strategic development of sustainable wind-based green hydrogen projects along Mauritania's coastline.

Keywords: Mauritania; site selection; multi-criteria decision making; analytic hierarchy process; evidential reasoning; green hydrogen

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1. Introduction

Carbon-neutral alternatives to fossil fuels are increasingly being pursued across a wide range of applications, reflecting the growing imperative to decarbonise energy systems. Among these, hydrogen is gaining significant global traction, with green hydrogen, in particular, is emerging as a promising carbon-neutral substitute for fossil fuels across multiple sectors. The global shift towards low-carbon energy systems has positioned green hydrogen as a key vector for decarbonisation across sectors such as industry, power generation, and transport. Unfortunately, most current hydrogen production systems still rely on fossil fuels, meaning that significant research and investment are required to develop more sustainable pathways for hydrogen generation. Mauritania, located on the western edge of the Sahara Desert and bordered by the Atlantic Ocean, offers substantial potential for renewable energy development, with an estimated area of 700,000 km^2 of land suitable for large-scale solar and wind power installations. The country's theoretical renewable energy potential is estimated at approximately 457.9 GW for solar photovoltaic and 47 GW for wind energy projects [1]. With a 750 km Atlantic coastline, the northern coastal corridor between Nouakchott and Nouadhibou has been identified as particularly favourable for wind energy development, with mean wind speeds ranging from 7.6 m/s to 9.8 m/s [2]. Despite this vast resource, Mauritania remains heavily dependent on fossil fuels, with 89% of its electricity produced from fossil fuels in 2021, followed by wind (6%) and solar PV (5%).

However, the country is making significant progress in adopting renewable energy. The 100 MW Boulanoir Wind Power Station represents Mauritania's largest wind farm and marks a step toward diversifying its energy mix and supporting future green hydrogen production. Mauritania's renewable energy portfolio currently consists of approximately 83 MW of solar and 130 MW of wind capacity. These installations form part of a broader national strategy to enhance the role of renewable energy sources within the national electricity mix [3]. According to the IEA's 2024 report, the majority of global green hydrogen projects at the construction stage or with a final investment decision (FID) are concentrated in China (around 45%) and Europe (around 30%). Nevertheless, Mauritania is emerging as a notable new player in this field. The country has signed several Memoranda of Understanding with leading international developers, such as CWP and London-listed Chariot Ltd. (London, UK), for large-scale hydrogen projects, including Nour and Aman [4]. In February 2025, the government further strengthened its position by concluding a framework agreement with GreenGo, a Danish developer, to develop the Megaton Moon project, providing access to 100,000 hectares of land [5]. The recently enacted Law no. 2024-037/P. R (Hydrogen Code) establishes a dedicated legal framework to attract investment, including tax incentives, the creation of the Mauritanian Green Hydrogen Agency, as well as clearly defined project obligations [6]. While this law provides the regulatory basis, Mauritania had already published a national green hydrogen roadmap in 2022, developed with AFRY Consulting, which envisions the country capturing approximately 1.5% of the global hydrogen demand and around 1% of the green steel market by 2050 [7].

In this context, the selection of suitable sites becomes a critical step in advancing green hydrogen development in Mauritania. While the country benefits from abundant wind and solar resources, other key factors such as levelised cost of hydrogen (LCOH), levelised cost of electricity (LCOE), payback period (PBP), accessibility to seaports and water resources, as well as environmental and social impacts, must be carefully assessed. A narrow focus on economic performance alone would provide a partial perspective and could overlook essential dimensions required for long-term sustainability and project feasibility. This underscores the need for comprehensive site selection methodologies that integrate economic, technical, environmental, and social criteria. For example, Yunna and Geng [8] used the Analytic Hierarchy Process (AHP) to rank potential locations for a solar–wind hybrid power station (SWHPS) in China, identifying the southwestern alternative as the optimal location, and the sensitivity analysis confirmed the robustness of the result. Similarly, in China, Zhao and Wang [9] used a geographic information system (GIS) combined with MCDM techniques to select the most suitable site for the construction of a wind–solar–hydrogen storage power plant. Their study confirmed that Location A6, in the Inner Mongolia Autonomous Region of China, was the optimal, again supported by sensitivity analysis. In Iran, Mostafaeipour and Sadeghi Sedeh [10] evaluated five major petrochemical complexes as potential sites for constructing a solar power plant to produce green chemical fertilisers.

Using a combination of AHP and the TODIM method, they identified the Shiraz Petrochemical Complex as the most suitable. Similarly, Loughney et al. [11] developed a methodology based on Evidential Reasoning (ER) to determine the optimal location for a floating offshore wind farm on the northern coast of Scotland. Their analysis found that Site 15, along with five other sites out of 45, represented the most promising candidates for development. In a related study, Diaz et al. [12] compared AHP with a hybrid AHP–ER approach for selecting floating offshore wind farm sites. They concluded that both methods are suitable for this decision-making problem, although the ER method is more efficient and requires fewer expert judgments, offering practical advantages in complex site-selection processes.

In southern Thailand, Ali et al. [13] employed a combined GIS approach and AHP to assess and select potential sites for solar-based green hydrogen production. Their analysis revealed that approximately 4302 km^2 in the southern region is highly suitable for deployment, with a further 3350 km^2 classified as moderately suitable. In Algeria, Tiar et al. [14] adopted a similar GIS and AHP methodology and identified around 4076 km^2 of highly suitable land for producing hydrogen.

In India, Thekkethil et al. [15] applied AHP to assess land suitability for establishing a green hydrogen hub across thirteen states, identifying Gujarat as the most suitable location, followed by Maharashtra and Andhra Pradesh. Likewise, in the Brazilian state of Ceará, Leal et al. [16] employed four MCDM techniques to rank municipalities for wind and solar-powered hydrogen production, finding that Araripe had the highest suitability among 184 municipalities.

Kumar et al. [17] developed a GIS-MCDM framework for the development of offshore green hydrogen systems in Australia, with sensitivity analysis confirming Site 3 as the most suitable location for offshore hybrid renewable-powered green hydrogen production in the marine region. Similarly, Rekik and El Alimi [18] applied GIS-MCDM techniques for selecting optimal sites for solar-based green hydrogen projects in Tunisia, highlighting the southeastern and southwestern regions, particularly Sfax, Monastir, and Sousse, as the most promising areas. Pinto et al. [19] further reinforced these findings using GIS-AHP, confirming the southern and eastern regions of Tunisia as highly suitable for solar-hydrogen production. In Cameroon, Metegam and Flora [20] applied GIS-AHP for evaluating the potential of solar and wind energy for both electricity and hydrogen production, concluding that 30.14% of the national territory is highly suitable, while 42.35% is unsuitable. In a related study, Flora and Metegam [21] used GIS-AHP to evaluate land suitability for five solar power system configurations. Their findings confirmed that 42.35% of the area is unsuitable for solar energy implementation. The study also revealed that the solar PV system ranked as the most favourable, followed by the solar PV and concentrated solar power hybridisation with wet and dry cooling.

Recent studies have proposed advanced heterogeneous MCDM approaches for site selection in various domains. For example, Wan et al. [22] applied complex heterogeneous MCDM methods to solar PV station site selection. Similarly, Wan et al. [23] introduced a heterogeneous MCDM framework combining a trapezoidal cloud model and MULTIMOORA method to determine optimal container multimodal transport routes. Additionally, Dong et al. [24] proposed a new MCDM approach with probabilistic linguistic term sets for hotel construction project site selection. These contributions highlight the increasing methodological sophistication in site selection research, particularly in handling heterogeneous information and group preferences. However, many of these approaches rely on problem-specific linguistic or cloud-based modelling, high computational complexity when the number of alternatives increases, and non-linear procedures, which may limit their scalability and applicability in data-scarce decision contexts. In contrast, the hybrid AHP–ER framework adopted in this study offers a transparent and flexible integration of quantitative and qualitative data with explicit uncertainty representation through belief-degree distributions, making it well-suited to strategic wind-based green hydrogen site selection.

The selection of the ER approach in this study is further supported by comparative evidence from the decision-making literature. Previous studies show that hybrid AHP–ER frameworks provide more transparent, robust, and reliable decision-support structures, particularly in complex site-selection contexts [12,25]. ER-based aggregation has also been shown to yield more reliable outcomes than simple additive approaches such as SAW [26]. Comparative assessments against conventional MCDM methods (AHP, ANP, TOPSIS, PROMETHEE, and clustering-based techniques) further highlight ER's strong performance in uncertainty handling and consistency, while maintaining moderate computational complexity and modelling effort [27]. These features make ER particularly suitable for strategic site selection in emerging, data-scarce contexts such as wind-based green hydrogen production.

Although numerous studies have employed MCDM methods to renewable energy and hydrogen planning projects, several important research gaps remain. First, there is a lack of context-specific analyses for Mauritania. While substantial research exists for Europe, Asia, and other parts of North Africa, Mauritania has received limited scholarly attention despite its exceptional wind potential, extensive coastline, and favourable proximity to export markets. Second, existing literature predominantly relies on single MCDM methods, such as the AHP method, which limits the ability to integrate heterogeneous (quantitative and qualitative) criteria and robustly handle uncertainty and imprecision inherent in expert judgments. The ER approach is specifically designed to overcome these limitations. However, despite its suitability for managing incomplete and uncertain information, the ER approach, particularly in a hybrid AHP–ER context, has not been applied to the complex multi-criteria problem of green hydrogen site selection. Consequently, its potential advantages in this strategic sector remain unexplored. Addressing these research gaps, this study presents a hybrid AHP–ER framework for selecting suitable locations for wind-based green hydrogen production in Mauritania, integrating both quantitative and qualitative criteria into a balanced and comprehensive assessment. This study represents one of the first structured MCDM applications to hydrogen site selection in Mauritania and offers policymakers and investors valuable decision-support insights by identifying the most promising coastal sites for future green hydrogen projects.

The main contributions of this paper are summarised as follows:

- A hybrid MCDM framework integrating the AHP and ER approach is proposed to support site selection for wind-based green hydrogen production.
- The framework enables the systematic integration of heterogeneous information while explicitly accounting for uncertainty and incomplete expert judgements through belief structures.
- The proposed approach is applied to a real-world case study along the northern coast of Mauritania, evaluating five coastal sites using region-specific technical, economic, environmental, and social indicators.

The remainder of this paper is organised as follows:

Following the introduction, which includes the literature review on the use of MCDM methods in the context of site selection in Section 1, Section 2 presents the proposed hybrid AHP–ER framework. Section 3 describes the case study area, criteria evaluation process, and the dataset used in this study. Section 4 presents and discusses the results, including ranking outcomes, sensitivity analysis, and validation of the process. Finally, Section 5 concludes the paper and highlights key findings, limitations of this paper, and the directions of future research.

2. Materials and Methods

MCDM methods can generally be divided into two main categories: Multi-Objective Decision-Making (MODM) and Multi-Attribute Decision-Making (MADM). MADM is typically used to evaluate and select the most suitable alternative(s) (e.g., sites, technologies, policies) based on multiple criteria. In contrast, MODM is used when optimising multiple conflicting objectives under constraints, usually involving continuous decision variables. MCDM frameworks incorporate several key factors depending on the specific nature of the decision-making problem. The main components are outlined below:

- The alternatives represent different possible courses of action or options under consideration.
- The criteria are the measurable characteristics used to evaluate and compare these alternatives.

This study applied a hybrid decision-making framework that combines AHP and ER. The objective was to evaluate and rank potential sites for wind-based green hydrogen production along Mauritania's northern coast: Nouakchott, Nouamghar, Tasiast, Boulanoir, and Nouadhibou.

2.1. The Proposed Hybrid Approach

The proposed framework is structured in three main stages. First, a hierarchical structure is developed, consisting of four main criteria (economic, technical, environmental, and social) and their respective sub-criteria. Second, the AHP method is applied to derive the relative weights of these criteria based on pairwise comparisons informed by expert judgment through a survey. Finally, the ER method is employed to evaluate and rank the five potential sites for wind-based green hydrogen production. The proposed hybrid framework procedure is illustrated in Figure 1. The approach consists of eight key steps, described as follows:

1. Define the problem.
2. Select the criteria.
3. Collect data to support expert evaluations.
4. Conduct the AHP survey to obtain pairwise comparison judgments and apply AHP to derive the weights of the criteria.
5. Conduct the ER survey to assign belief degrees for each alternative based on the criteria.
6. Run the ER algorithm separately for each alternative using IDS software (Version 1.2).
7. Rank the alternatives.
8. Conduct sensitivity analysis and axioms validation of the ER model to test both the decision process and the stability of results.

2.2. Analytic Hierarchy Process (AHP) for Criteria Weighting

AHP, introduced by Saaty [28], is a structured MCDM method that derives criteria weights through pairwise comparisons. The methodology involves constructing a hierarchical representation of the decision problem and systematically comparing criteria using Saaty's fundamental scale of relative importance used for the AHP, as shown in Table 1.

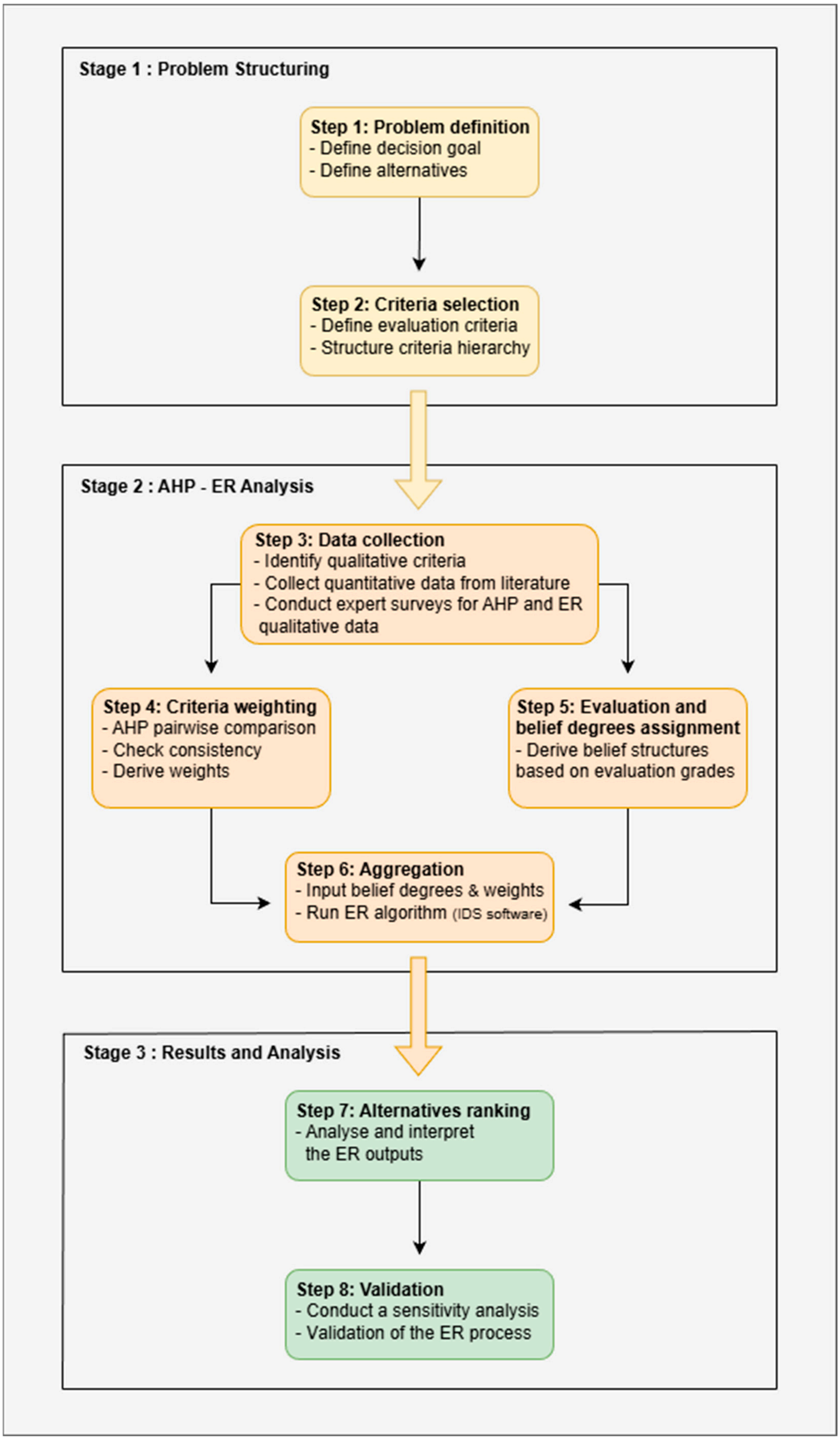

Figure 1. The overall framework for site selection assessment.

Table 1. Weighting scale of the relative importance [28].

Numerical Weighting	Explanation
1	Equally important
3	A little important
5	Important
7	Very important
9	Extremely important
2, 4, 6, 8	Intermediate values
1/2, 1/3, 1/4, 1/5, 1/6, 1/7, 1/8, 1/9	Values for inverse comparison

The pairwise judgments in AHP are represented by $n \times n$ matrix A, as shown in Equation (1) [28–30].

$$A = (a_{ij}) = \begin{bmatrix} 1 & a_{12} & \dots & a_{1n} \\ 1/a_{12} & 1 & \dots & a_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ 1/a_{1n} & 1/a_{2n} & \dots & 1 \end{bmatrix} \quad (1)$$

where $i, j = 1, 2, 3, \ldots, n$ and each element a_{ij} represents the relative importance of criterion i over criterion j.

For a comparison matrix of order n, $(n \times (n - 1)/2)$ evaluations are required. The resulting weight vector reflects the relative importance of each element in the pairwise comparison matrix with respect to its overall contribution to the decision-making process and can be calculated using Equation (2) [14,30].

$$\omega_k = \frac{1}{n}\sum_{j=1}^{n}\left(\frac{a_{kj}}{\sum_{i=1}^{n} a_{ij}}\right) \qquad (k = 1, 2, 3, \ldots, n) \quad (2)$$

where each a_{ij} denotes the element in row i and column j of a comparison matrix of order n.

To verify reliability, the Consistency Ratio (CR) is determined, as shown below in Equations (3)–(5), given by [12,14,28–30].

$$CR = \frac{CI}{RI} \quad (3)$$

with the Consistency Index (CI) defined as:

$$CI = \frac{\lambda_{max} - n}{n - 1} \quad (4)$$

$$\lambda_{max} = \frac{1}{n}\sum_{j=1}^{n}\left(\frac{a_{kj}}{\sum_{i=1}^{n} a_{ij}}\right) \quad (5)$$

where λ_{max} is the matrix's maximum eigenvalue, n is the number of criteria, and RI is the random index, whose value is selected according to the size of the pairwise matrix, as presented in Table 2.

Table 2. The Random Index [28].

n	1	2	3	4	5	6	7	8	9	10
RI	0.00	0.00	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49

If the result of CR is less than 0.1, the calculated weights are accepted as valid. Otherwise, the comparison process must be repeated.

2.3. Evidential Reasoning (ER) for Site Evaluation

The ER approach introduced by Yang and Singh [31] is designed to evaluate alternatives involving both quantitative and qualitative criteria while explicitly accounting for uncertainty and incomplete information [11,12,31–35].

The implementation of the ER algorithm can be carried out through five steps, as outlined below:

Step 1: Definition of evaluation grades.

A common set of linguistic evaluation grades is defined for all criteria to ensure consistency across expert assessments.

Step 2: Assignment of belief degrees.

For each alternative and criterion, experts express their assessments through a questionnaire by distributing belief degrees across the predefined evaluation grades.

Step 3: Generate basic probability masses.

The assigned belief degrees are transformed into basic probability masses, taking into account the relative importance of criteria derived from the AHP weighting process.

Step 4: Generate combined belief degrees.

The probability masses are recursively combined using the ER aggregation process to obtain an overall belief distribution for each alternative.

Step 5: Utility calculation and ranking.

The aggregated belief distributions are converted into expected utility values, enabling the final ranking of candidate sites.

2.3.1. ER Algorithm

In the ER framework, each alternative is assessed through belief degrees distributed across five evaluation grades, as shown in Equation (6) [11,12,31–35].

$$H_n = \{Worst\ (H_1),\ Poor\ (H_2),\ Average\ (H_3),\ Good\ (H_4),\ Best\ (H_5)\} \tag{6}$$

Each sub-criterion e_i is evaluated using a distributed assessment $S(e_i)$, represented by belief degrees $\beta_{n,i}$ associated with the evaluation grades H_n. This representation is illustrated in Equation (7) [11,12,32–34].

$$S(e_i) = \{(H_n, \beta_{n,i})\ n = 1, 2 \ldots N\} \tag{7}$$

where $\beta_{n,i}$ denotes the belief degrees allocated to the evaluation grades H_n.

The ER algorithm transforms the distributed assessments into the basic probability masses $m_{n,i}$, which are determined using Equations (8) and (9) [11,12,32–34].

$$m_{n,i} = \omega_i \beta_{n,i}\ n = 1, 2 \ldots N \tag{8}$$

$$m_{H,i} = 1 - \sum_{n=1}^{N} m_{n,i} = 1 - \omega_i \sum_{n=1}^{N} \beta_{n,i} \tag{9}$$

where ω_i denotes the weight of the ith sub-criteria (e_i) and $m_{H,i}$ represents the remaining probability mass not distributed among the individual grades after evaluating all grades.

These probability masses are then recursively aggregated using the ER algorithm to generate combined probability masses, as shown in Equations (10)–(12) [11,12,32–34]. To present the ER aggregation process, we must also define the subset of the i sub-criteria under the Ith main criterion as $E_{I(i)} = \{e_1 e_2 \cdots e_i\}$.

$$m_{n,I(i+1)} = K_{I(i+1)}\left(m_{n,I(i)}m_{n,i+1} + m_{n,I(i)}m_{H,i+1} + m_{H,I(i)}m_{n,i+1}\right) \tag{10}$$

$$m_{H,I(i+1)} = K_{I(i+1)}m_{H,I(i)}m_{H,i+1} \tag{11}$$

$$K_{I(i+1)} = \left[1 - \sum_{t=1}^{N}\sum_{j=1}^{N} m_{t,I(i)}m_{j,i+1}\right]^{-1} \tag{12}$$

where $K_{I(i+1)}$ is the normalising factor with $m_{n,I(1)} = m_{n,1}$ and $m_{H,I(1)} = m_{H,1}$ so that $\sum_{n=1}^{N} m_{n,I(i+1)} + m_{H,I(i+1)} = 1$.

Once the probability masses are aggregated, the combined belief degrees β_n are calculated using Equations (13) and (14) [11,12,32–34].

$$\beta_n = \frac{m_{n,I(L)}}{1 - m_{H,I(L)}} \; n = 1, 2 \ldots N \tag{13}$$

$$\beta_H = 1 - \sum_{n=1}^{N} \beta_n \tag{14}$$

where β_n represents the combined belief degree of the aggregated assessment and β_H denotes the unassigned belief degree considering all L attributes.

When alternatives cannot be ranked directly based on their distributed assessments, an estimated utility $U(H_n)$ is introduced. In the absence of preference information, these utility values are typically assumed to be equidistant, as defined by Equation (15) [11,12,33,35].

$$U(H_n) = \{U(H_1) = 0, U(H_2) = 0.25, U(H_3) = 0.5, U(H_4) = 0.75, U(H_5) = 1\} \tag{15}$$

The estimated utility of the main criteria y, evaluated through a set of sub-criteria e_i, and corresponding evaluation grades, is calculated using Equation (16) [11,12,32–35].

$$U(S(y(e_i))) = \sum_{n=1}^{N} U(H_n)\beta_n(e_i) \tag{16}$$

2.3.2. Validation of the ER Process

Nevertheless, the aggregation procedure described above may not be rational or provide meaningful results unless it satisfies a set of established synthesis axioms. Therefore, validating the decision-making process is essential, providing confidence in the robustness and reliability of the results. According to recent literature, an axiom-based validation procedure is commonly applied to verify the integrity of the ER process [11,12,34]. The four axioms to be examined in this study are as follows:

Axiom 1. *If none of the sub-criteria are assigned to evaluation grade H_n, the main criterion must also not be assigned to H_n.*

Axiom 2. *If all sub-criteria are assigned to evaluation grade H_n, then the main criterion must be precisely assigned to H_n.*

Axiom 3. *If all sub-criteria are completely assigned to a given subset of evaluation grades, the main criterion must likewise be assigned to the same subset of evaluation grades.*

Axiom 4. *If the assessment of any sub-criterion is incomplete, then the evaluation of the main criterion must also contain a corresponding level of incompleteness.*

The Intelligent Decision System (IDS) is a software tool based on the Evidential Reasoning (ER) approach described by Xu and Yang [33]. IDS integrates multiple decision-making tools, including the AHP for deriving criteria weights and the ER algorithm for aggregating both quantitative and qualitative assessments from the sub-criteria level to the overall decision objective.

In this study, the proposed hybrid AHP–ER framework was implemented using the IDS, enabling systematic modelling, evaluation, and comparison of the selected alternatives.

3. Case Study: Northern Coast of Mauritania

3.1. Study Area and Selected Sites

The study utilised data collected from multiple coastal sites located between Nouakchott and Nouadhibou. In the Nouakchott region, measurements were obtained from a mast situated approximately 28 km south of the city along the Rosso-Nouakchott corridor. The coordinates of all measurement points and the corresponding wind speed (WS) sensor heights are provided in Table 3, mapped in Figure 2, and complemented by site photographs in Figure 3. At Nouamghar, wind resource data were derived through advanced satellite-based modelling, processed by 3Tier, a recognised global provider of high-resolution wind resource assessment services. The approach integrates satellite observations with mesoscale atmospheric modelling, offering robust and high-fidelity wind estimates. At the Tasiast site, vertical wind profiles were obtained using a ZX300 LiDAR unit (Zephir Ltd., Malvern, UK) installed inside a container equipped with photovoltaic panels and battery storage backup. Although more costly than conventional meteorological towers, this configuration provides significant advantages, including portability and the capability of measuring the WS at ten different heights. In Boulanoir, a meteorological mast installed in 2021 as part of the 100 MW wind farm project was fitted with sensors for wind speed, wind direction, temperature, atmospheric pressure, and relative humidity. Measurements were collected every second and aggregated into ten-minute averages. Additional masts at Boulanoir and Nouadhibou were equipped with thermometers, anemometers, and wind vanes, all mounted with protective covers.

Table 3. Identification of measurement masts.

Sites	Location	Station	GPS Coordinates
1	Nouakchott	Measurement Mast (Helimax Energy Inc., Montréal, QC, Canada)	17°58′02.80″ N, 15°58′52.10″ W
2	Nouamghar	3Tier Satellites (Vaisala, Vantaa, Finland)	19°33′44.49″ N, 15°55′27.57″ W
3	Tasiast	ZX300 Lidar	20°31′36.85″ N, 15°59′29.44″ W
4	Boulanoir	Measurement Mast	21°16′29.07″ N, 16°47′08.98″ W
5	Nouadhibou	Measurement Mast	20°53′59.70″ N, 17°03′36.10″ W

Furthermore, several strategic reference points were identified to anchor the spatially-based quantitative criteria. These include the Port of Nouakchott and the Port of Nouadhibou, the country's primary industry and export hubs, which are critical for equipment transport and future hydrogen export. Environmental considerations were also integrated by incorporating two protected areas within the study region: the Diawling and Banc d'Arguin National Parks.

Figure 2. Positions of meteorological masts throughout Mauritania.

Figure 3. Images of meteorological measurement masts located in Mauritania.

3.2. Criteria Evaluation

This study aimed to identify the most suitable site for wind-based green hydrogen production along the northern coast of Mauritania (Nouakchott, Nouamghar, Tasiast, Boulanoir, and Nouadhibou). The evaluation was conducted using a hybrid multi-criteria decision-making framework that integrates the AHP and ER. Four primary criteria (economic, technical, environmental, and social), along with their respective sub-criteria (Table 4), were used to support a holistic and robust assessment.

Table 4. List of criteria.

Main Criteria	Sub-Criteria	References
Economic	LCOH LCOE PBP	[17,36,37] [29,37,38] [8,9,29,39]
Technical	Wind availability Proximity to water Distance from seaports	[8,11,12,16,39] [12,13,18–21] [10,12,17]
Environmental	Annual reduction of CO_2 emissions Distance from protected areas Distance from residential areas	[17,29,37–39] [12,13,18,19] [12,13,18–21]
Social	Job creation Health & Safety Public acceptance	[3,30,38,39] [17,30,36] [8,17,30,36,38,39]

The criteria were selected to ensure a balanced representation across all dimensions, thereby supporting a comprehensive and holistic evaluation. These criteria align with the most relevant factors identified in the existing literature on green hydrogen site selection. It is important to note that criteria selection is context-dependent and may vary depending on the project's objectives, regional characteristics, and stakeholder priorities. Accordingly, the proposed framework remains flexible and can be applied to different configurations of criteria and alternatives depending on the specific decision-making problem. In this study, these criteria will be applied, with a specific focus on selecting the best location for hydrogen production from wind energy. A detailed description of these criteria is presented in the form of sub-criteria in Table 5.

Table 5. Criteria for MCDM analysis with their annotation and description.

Main Criteria	Sub-Criteria	Description
Economic (x)	LCOH (e_1)	The average production cost of hydrogen throughout the plant's lifetime.
	LCOE (e_2)	The average cost of producing electricity used for hydrogen production.
	PBP (e_3)	The number of years required to recover the initial investment in the green hydrogen production project.
Technical (y)	Wind availability (e_4)	The reliability and consistency of wind resources at the project site for hydrogen production.
	Water proximity (e_5)	The distance of the project site from a water source required for hydrogen production.
	Distance from seaports (e_6)	The distance of the project site from the nearest seaport for equipment transport and future hydrogen export.
Environmental (z)	Annual reduction in CO_2 emissions (e_7)	The yearly amount of CO_2 emissions avoided by replacing fossil-based energy with wind-powered green hydrogen.
	Distance from protected areas (e_8)	The distance of the project site from ecologically sensitive or legally protected zones.
	Distance from residential areas (e_9)	The distance of the project site from residential areas considering noise, visual disturbance, and safety concerns.
Social (v)	Job creation (e_{10})	The employment opportunities created during the construction and operational phases of the project.
	Health & Safety (e_{11})	The potential risks associated with the hydrogen production facility.
	Public acceptance (e_{12})	The level of community support for approving the project.

In this study, a hierarchical structure was developed comprising four levels: goal, main criteria, sub-criteria, and alternatives, as illustrated in Figure 4.

Level 0: Goal

To select the most suitable location among the candidate sites for wind-based green hydrogen production.

Level 1: Main Criteria

The main criteria considered in this study were economic, technical, environmental, and social.

Level 2: Sub-criteria

The sub-criteria considered in this study were LCOH, LCOE, PBP, wind availability, proximity to water, distance from seaports, annual reduction of CO_2 emissions, distance from protected areas, distance from residential areas, job creation, health & safety, and public acceptance.

Level 3: Alternatives

The following sites will be compared and analysed:

S1—Nouakchott

S2—Nouamghar

S3—Tasiast

S4—Boulanoir

S5—Nouadhibou

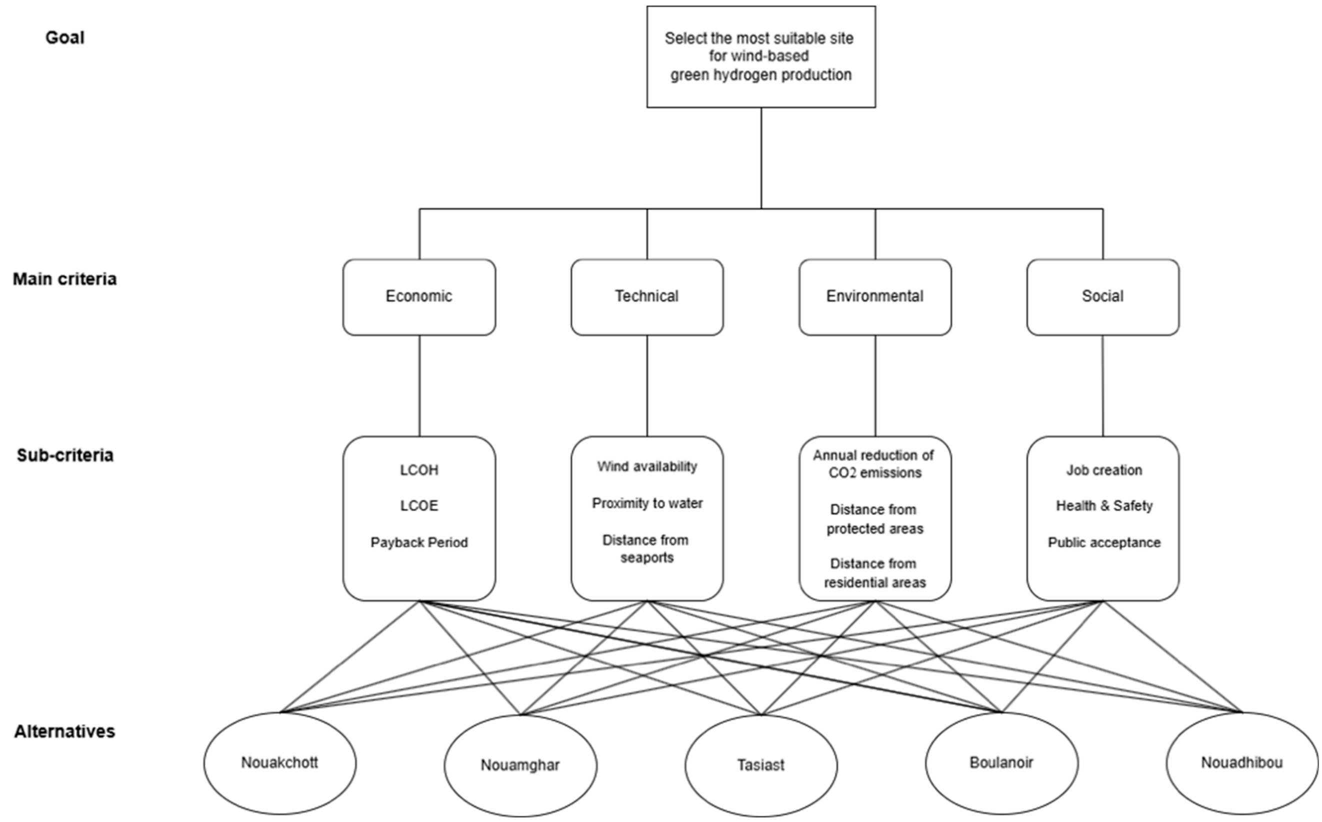

Figure 4. The hierarchical structure of the study.

3.3. Data Collection

A structured questionnaire was used to gather data from eight academic and professional experts in sustainable energy and renewable energy technologies in Mauritania. While the experts remain anonymous, their areas of expertise are presented in Table 6.

Table 6. List of experts and their professional background.

	Position	Type of Organisation	Experience
Expert 1	O&M Solar Engineer	Industrial mining operations	5 years–10 years
Expert 2	Dr/Electrical Engineer	Academic institution	>10 years
Expert 3	Dr/Energy Specialist	International development finance institution	>10 years
Expert 4	Energy Specialist	Government energy regulatory body	5 years–10 years
Expert 5	Professor in Applied Physics	Academic institution	>10 years
Expert 6	Professor in Applied Physics	Academic institution	>10 years
Expert 7	Professor/Director of Scientific Programs	National research and innovation agency	>10 years
Expert 8	Professor of Physics and Materials Science	Academic institution	>10 years

All experts completed the questionnaire, providing both the pairwise comparison judgements for the AHP weighting process and the belief degree assessments for each sub-criterion's evaluation. Additional required data were obtained from relevant literature and other secondary sources. These data, summarised in Table 7, were adapted for use in this study.

Table 7. Assessment of the sub-criteria for all sites.

Sub-Criteria	S1	S2	S3	S4	S5	Source
LCOH (USD cents/kg H_2)	270.05	259.75	256.88	214.7	188.02	[2]
LCOE (USD cents/kWh)	8.93	8.59	8.75	7.10	6.22	[2]
PBP (Years)	3.3	3.3	3.2	3.3	4.7	[2]
Wind availability	(0.04, 0.10, 0.14, 0.32, 0.40)	(0.09, 0.10, 0.16 0.29, 0.36)	(0.08, 0.14, 0.24, 0.32, 0.22)	(0.08, 0.09, 0.12, 0.26, 0.45)	(0.00, 0.01, 0.08, 0.21, 0.70)	Expert survey
Proximity to water (Km)	4.181	49.84	40.28	18.89	0.611	Google Earth database
Distance from seaports (Km)	5.168	174.1	173.14	61.48	0.765	Google Earth database
Annual reduction of CO_2 emissions ($MtCO_2$/year)	2661.29	2766.84	2819.62	3347.39	3822.38	[2]
Distance from protected areas (Km)	163.75	119.73	28.32	93.19	90.5	Google Earth database
Distance from residential areas (Km)	0.355	7.382	14.43	14.33	0.874	Google Earth database
Job creation	(0.02, 0.04, 0.06, 0.18, 0.70)	(0.10, 0.14, 0.18, 0.16, 0.42)	(0.10, 0.13, 0.19, 0.20, 0.38)	(0.08, 0.09, 0.09, 0.21, 0.53)	(0.00, 0.01, 0.09, 0.22, 0.68)	Expert survey
Health & Safety	(0.05, 0.18, 0.25, 0.22, 0.30)	(0.10, 0.22, 0.26, 0.22, 0.20)	(0.09, 0.22, 0.24, 0.19, 0.26)	(0.09, 0.21, 0.19, 0.22, 0.29)	(0.03, 0.15, 0.23, 0.24, 0.35)	Expert survey
Public acceptance	(0.06, 0.12, 0.18, 0.27, 0.37)	(0.11, 0.22, 0.24, 0.20, 0.23)	(0.09, 0.18, 0.23, 0.22, 0.28)	(0.10, 0.21, 0.21, 0.24, 0.24)	(0.04, 0.06, 0.15, 0.32, 0.43)	Expert survey

The evaluation draws on a combination of expert survey responses and secondary data sources. Economic and environmental indicators such as the LCOH, LCOE, PBP and annual reduction in CO_2 emissions were obtained from a previous techno-economic assessment of wind-based hydrogen projects in Mauritania, in which the candidate sites were evaluated using wind resource and cost data from 2022–2023. In that assessment, the indicators were calculated under uniform system boundaries, covering wind electricity generation for hydrogen production, with identical technology assumptions, including a commercial onshore wind turbine (Gamesa G114–2.5 MW) and alkaline electrolysis representative of current industrial practice. Technical and environmental sub-criteria, including distance from protected areas, proximity to water resources, and distance from seaports, were derived from geospatial databases. The remaining sub-criteria were assessed qualitatively using expert judgements. Each sub-criterion was defined with corresponding performance grading scales to enable both qualitative and quantitative comparison across the five candidate sites. To ensure transparency and consistency, all experts were provided with a unified evaluation protocol and a common set of performance grading definitions prior to completing the questionnaires.

4. Results and Discussion

4.1. Ranking Results

The IDS software was used to carry out the computational steps of AHP and derive the criteria weights. The final weights of the main criteria and associated sub-criteria, obtained through the AHP method described above, are summarised in Table 8 and illustrated in Figure 5.

Table 8. Final weights of the criteria.

Main Criteria	Weight	Sub-Criteria	Weight
Economic	0.3226	LCOH	0.4642
		LCOE	0.3063
		PBP	0.2295
Technical	0.2093	Wind availability	0.3852
		Proximity to water	0.2911
		Distance from seaports	0.3237
Environmental	0.2949	Annual reduction of CO_2 emissions	0.4269
		Distance from protected areas	0.3668
		Distance from residential areas	0.2063
Social	0.1732	Job creation	0.1812
		Health & Safety	0.5173
		Public acceptance	0.3015

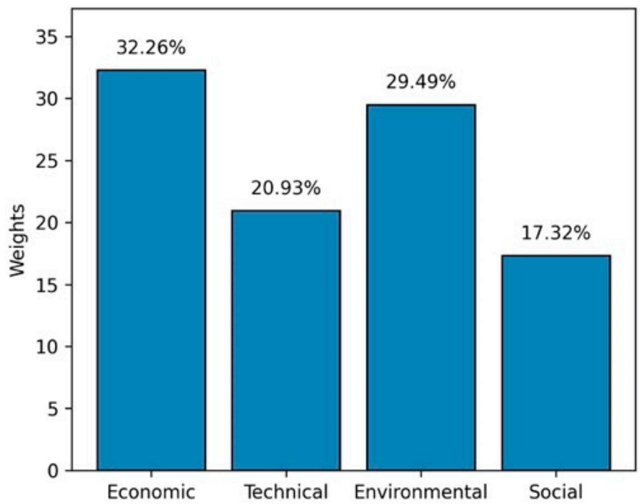

Figure 5. The weights of the main criteria.

The CR value obtained in this study was less than 0.1, suggesting that the experts' evaluations were acceptably consistent.

The results (Figure 5) indicate that the Economic criterion holds the highest importance (32.26%), followed by the Environmental (29.49%), Technical (20.93%), and Social (17.32%) criteria. This suggests that Techno-economic factors remain dominant in decision-making for green hydrogen projects, although environmental aspects are gaining notable significance.

The data from Table 7 were processed with the IDS software. The results obtained are summarised in Table 9 and illustrated in Figures 6–8.

Table 9. The utility scores and ranking of the alternatives.

Alternative	U (Total)	Ranking
S1: Nouakchott	0.4217	3
S2: Nouamghar	0.3227	4
S3: Tasiast	0.2890	5
S4: Boulanoir	0.6620	2
S5: Nouadhibou	0.8323	1

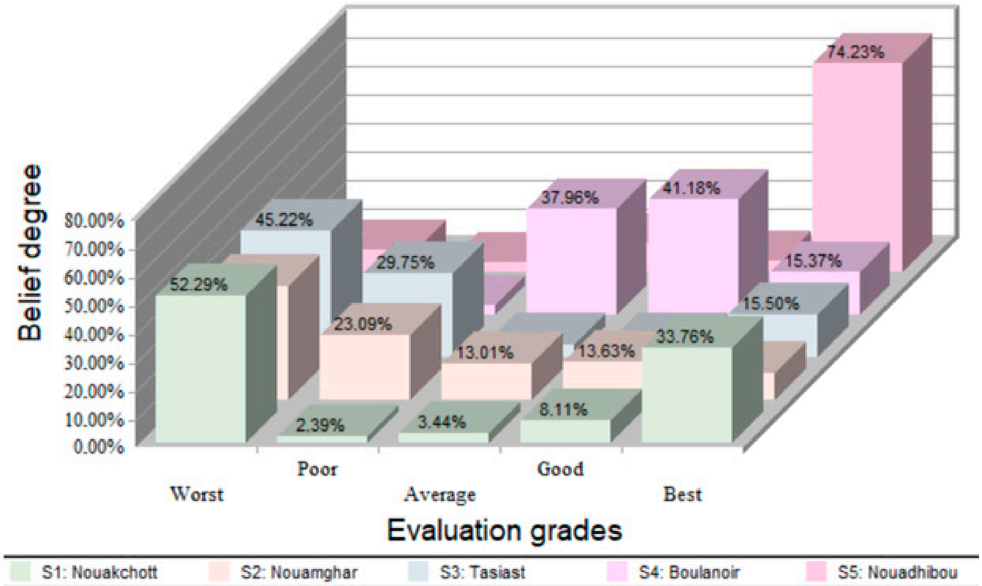

Figure 6. The aggregated belief degree distributions of the alternatives.

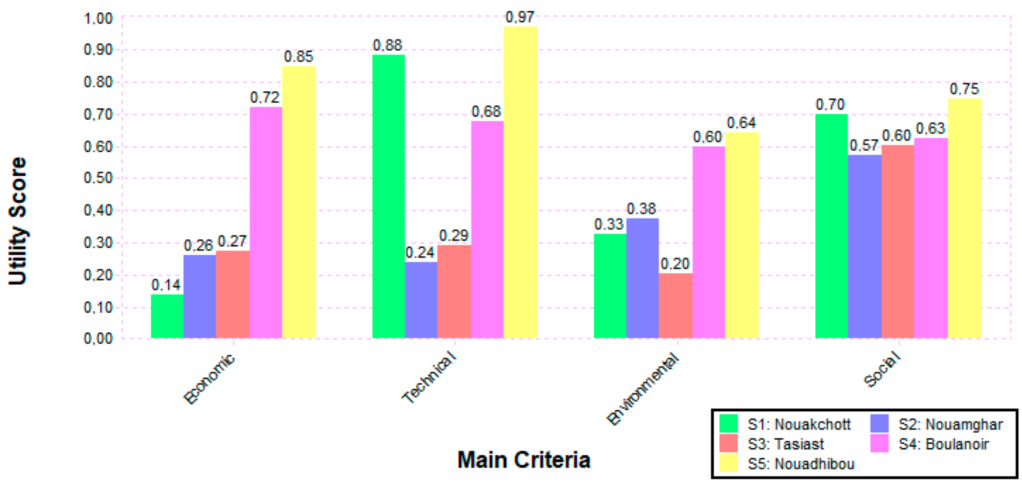

Figure 7. The utility scores of the main criteria for each alternative.

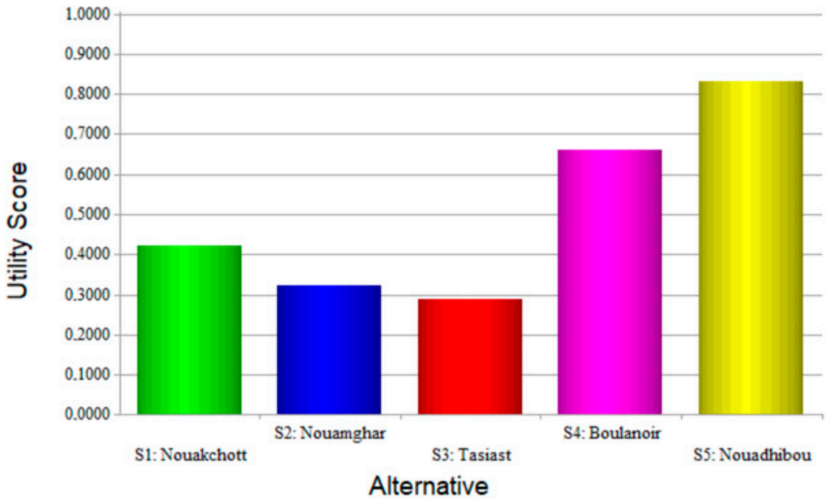

Figure 8. The overall utility scores of the alternatives.

Figure 6 presents the aggregated belief degree distribution for each alternative. The results indicate that Nouadhibou achieved the highest belief degree in the "Best" grade (74.23%), followed by Nouakchott (33.76%), Tasiast (15.50%), Boulanoir (15.37%), and finally Nouamghar (9.77%). However, Nouadhibou also recorded the lowest belief degree value (4.05%) for the "Good" grade, ranks third for "Average" grade (10.26%), and fourth in both "Poor" (3.36%) and "Worst" (8.10%) grades, indicating a more polarised evaluation profile than the other locations.

Despite these graphical results, the belief distributions alone do not provide a definitive ranking. In order to allow for numerical comparison of the alternatives, the given evaluations were converted into comparable utility scores using an equidistant utility scale (Worst = 0.0, Poor = 0.25, Average = 0.5, Good = 0.75, Best = 1.0). According to this transformation, the utility scores were calculated for each site. The resulting utility scores for each site are illustrated in Figures 7 and 8.

Figure 7 presents the utility score of each site across the main evaluation criteria considered in this study. The results clearly indicate that Nouadhibou ranked first for all the main criteria. In particular, it achieved the best score for the Technical (0.97) and Economic criteria (0.85), confirming its outstanding techno-economic viability.

Finally, the aggregated utility scores and final ranking of all alternatives are presented in Figure 8 and Table 9. The results show that Nouadhibou is the most suitable site for hydrogen production, achieving the highest overall score (0.8323), followed by Boulanoir (0.6620), Nouakchott (0.4217), Nouamghar (0.3227), and Tasiast (0.2890). These findings demonstrate that Nouadhibou offers the most balanced performance across sustainability dimensions, reinforcing its strategic potential as the most competitive site for green hydrogen production.

4.2. Discussion

The application of the hybrid AHP–ER framework had a clear influence on the ranking outcomes obtained in this study. By combining AHP weighting process with the ER aggregation process, the proposed model demonstrates a high degree of flexibility in handling heterogeneous quantitative and qualitative information while explicitly accounting for uncertainty in expert judgement. This capability is particularly relevant for strategic green hydrogen site selection, where data availability is limited and expert judgement plays a central role.

The ranking results indicate that Nouadhibou consistently outperformed the other candidate sites, a finding that aligns with a previous site selection study conducted in [2]. The convergence of results reinforces the credibility and robustness of the proposed framework.

In contrast, lower-ranked sites exhibited constraints in one or more critical dimensions. For example, Tasiast and Nouamghar performed well in the social dimension but were penalised by weaker economic and technical scores. Similarly, Nouakchott demonstrated strong technical and social performance, but its relatively lower economic and environmental scores limits its overall utility. This outcome highlights the importance of balanced multi-criteria performance rather than dominance in a single dimension.

4.3. Sensitivity Analysis

To ensure the credibility of the proposed framework, a sensitivity analysis was performed to evaluate the robustness of the final ranking with respect to variations in the weights of the main criteria (Economic, Technical, Environmental, and Social) and their effects on the ranking of alternative site outcomes. In this analysis, the weight of each main criterion was individually adjusted by −25%, −15%, 15%, and 25%, while the remaining criteria were proportionally modified to maintain a total weight of one. For each modified weight scenario, the IDS software recalculated the overall utility scores for the alternatives. The corresponding results are illustrated in Figures 9–12.

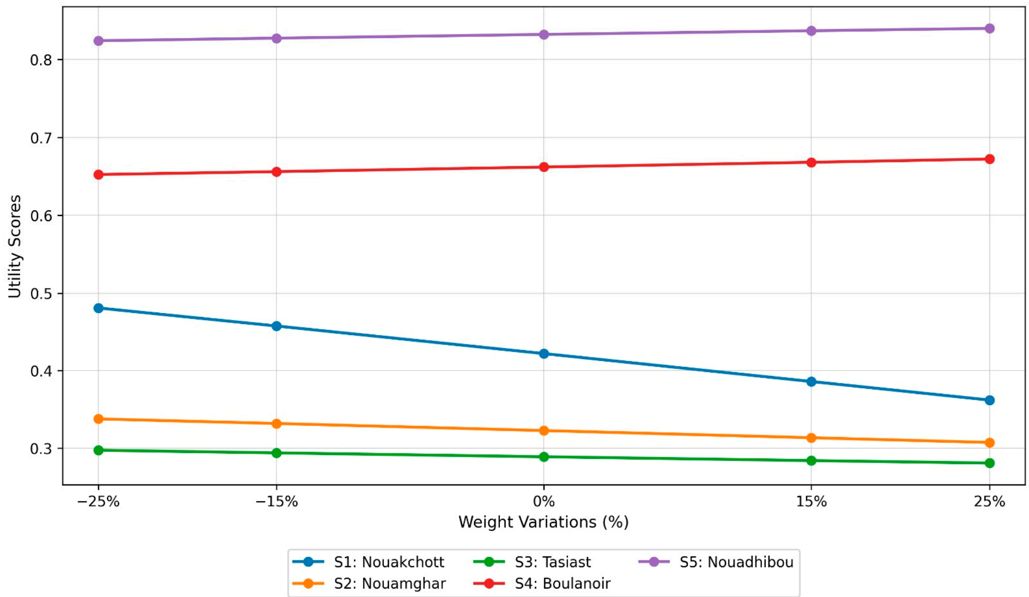

Figure 9. Impact of economic criteria weight variations on the utility scores of the alternatives.

The analysis revealed that the ranking of the alternatives remained stable across all tested variations, and the ranking results were still S5 > S4 > S1 > S2 > S3. While the overall ranking remained unchanged, the magnitude of utility score variations differed among the candidate sites. For instance, changes in the weight of the economic criterion (Figure 9) had a more pronounced effect on the utility score of Nouakchott. This behaviour reflects Nouakchott's relatively balanced but non-dominant economic performance (Figure 7), making its overall score more sensitive to variations in the economic weight. In contrast, Nouadhibou exhibited limited sensitivity due to its consistently strong performance across the economic dimension. Similar patterns were observed for technical, environmental, and social criteria, where sites that rely more heavily on a specific criterion displayed greater responsiveness to weight variations.

Overall, the results demonstrate that the proposed framework is both consistent and reliable for MCDM in green hydrogen site selection, without prescriptive policy recommendations.

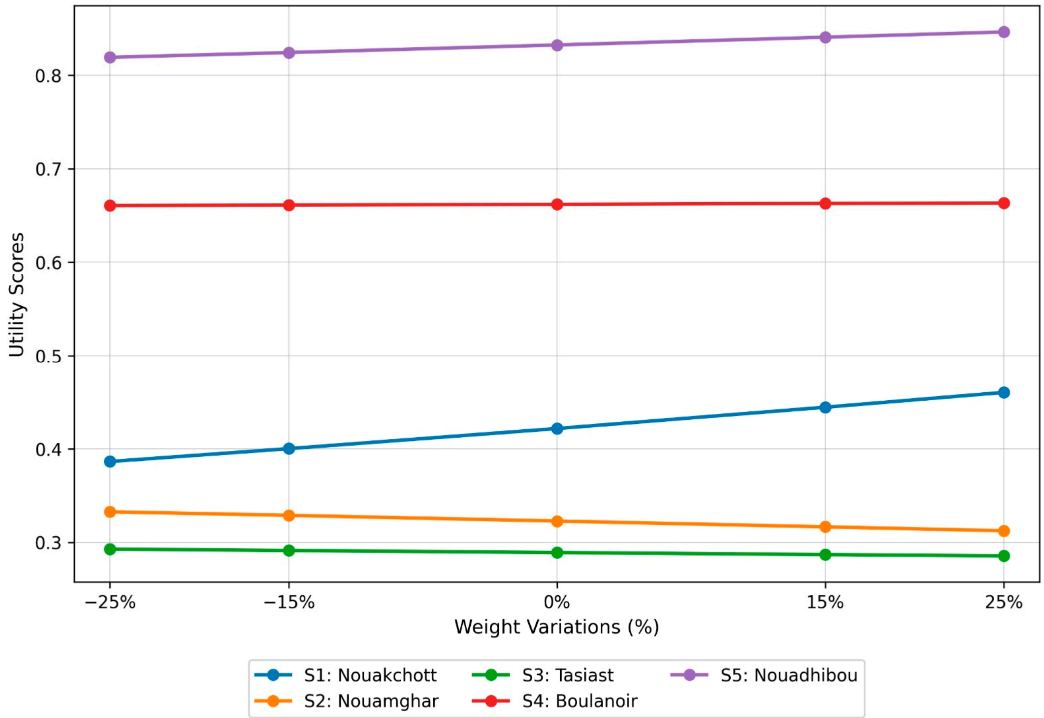

Figure 10. Impact of technical criteria weight variations on the utility scores of the alternatives.

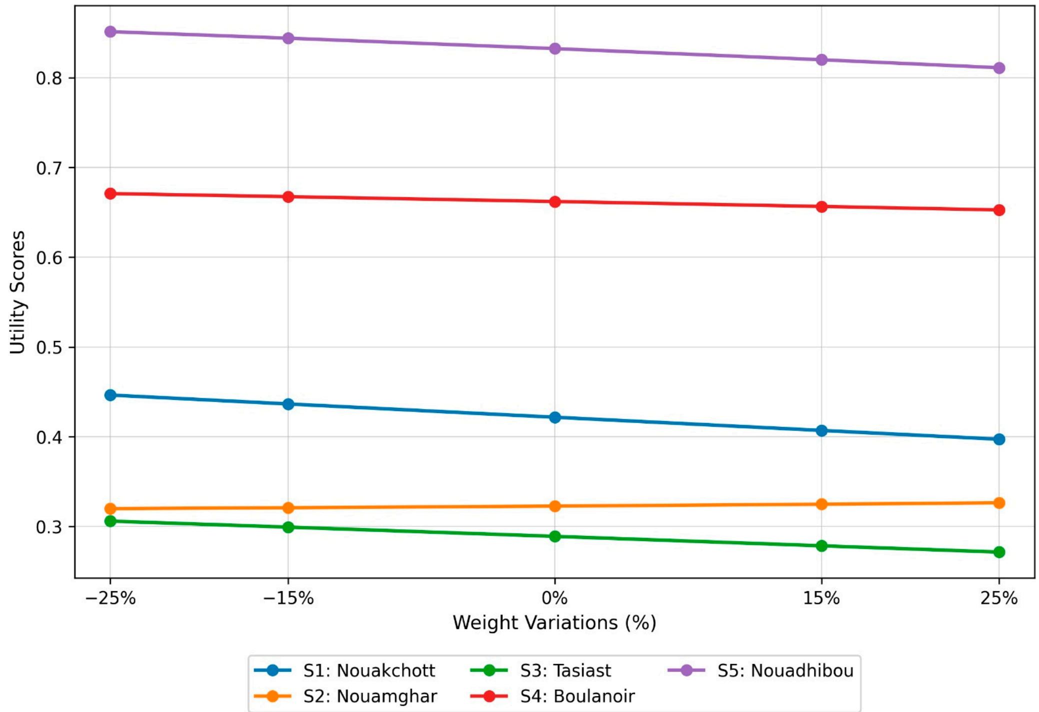

Figure 11. Impact of environmental criteria weight variations on the utility scores of the alternatives.

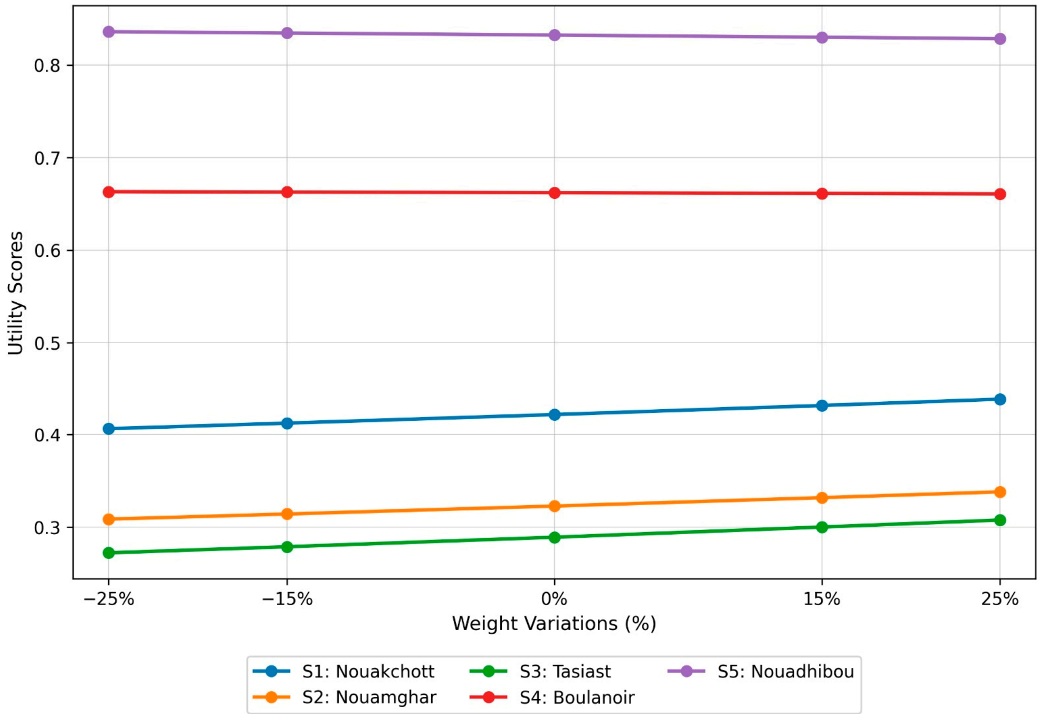

Figure 12. Impact of social criteria weight variations on the utility scores of the alternatives.

4.4. Validation of the ER Process

In addition, the ER aggregation process was evaluated against the four axioms outlined in Section 2.3 to provide partial methodological validation. The analysis confirms that all four axioms were satisfied in the study, demonstrating internal consistency in the evaluation process. Each axiom was examined individually as follows:

Axiom 1. *This axiom was satisfied. For the aggregation of the Environmental criterion at Site 4, none of the sub-criteria were assessed as "Worst". As a result, the belief degree associated with the "Worst" grade of the main criterion should also be 0, which it is.*

Axiom 2. *This axiom was satisfied for the Environmental criterion at Site 4. The sub-criteria (e7, e8, e9) all exhibited zero belief degrees in the "Worst" grade, leading to an aggregated "Worst" value of 0. The final aggregated belief distribution for this criterion was: "Worst" (0), "Poor" (0.265), "Average" (0.6836), "Good" (0.1525), and "Best" (0.1374), thereby confirming compliance with this axiom.*

Axiom 3. *This condition was fulfilled throughout the analysis, as all criteria were evaluated against the same set of grades: "Worst", "Poor", "Average", "Good", and "Best".*

Axiom 4. *This axiom was also satisfied since all belief degrees were complete, and the total belief for each criterion summed to one.*

Beyond procedural verification, the ER axiom-based validation process was employed to clarify the applicability conditions and limitations of the ER algorithm. Verifying these axioms ensures that the aggregation behaviour of the ER model is logically sound and the resulting decision outcomes are credible. However, this validation process does not eliminate uncertainty inherent in expert-based inputs, nor does it imply applicability beyond the specific decision context examined in this study.

On this basis, the ER-based aggregation process can be considered methodologically sound and appropriately validated for the site selection problem addressed in this study.

5. Conclusions

In this study, a hybrid AHP–ER decision-making framework was developed to identify suitable sites for wind-based green hydrogen development along the northern coast of Mauritania. Five coastal locations were evaluated using a structured hierarchy comprising four main criteria (Economic, Technical, Environmental, and Social) and associated twelve sub-criteria. The AHP method was employed to derive the relative importance of the criteria, while the ER method integrated heterogeneous quantitative and qualitative assessments to generate overall utility scores to rank the candidate sites. The results indicate that Nouadhibou (Site 5) is the highest-ranked location for wind-based green hydrogen development, followed by Boulanoir (Site 4), Nouakchott (Site 1), Nouamghar (Site 2), and Tasiast (Site 3). Nouadhibou demonstrated superior performance across all sustainability dimensions, particularly in economic and technical aspects, confirming its strong potential for large-scale green hydrogen production. Sensitivity analysis further validated the robustness of the rankings, with Nouadhibou consistently preserving its top position in the different weighting variation scenarios. The model was also shown to be valid with respect to the four ER axioms, ensuring the consistency and rationality of the aggregation.

Beyond its methodological contribution, this study provides a practical decision-support tool to inform Mauritania's emerging green hydrogen strategy. The proposed AHP–ER framework is flexible and can be adapted to other renewable energy planning scenarios or regional studies, particularly in regions where data availability is limited.

Despite these contributions, several limitations should be acknowledged. The analysis relies partly on expert-based weighting and belief assignments, which may reflect subjective judgements influenced by expert experience. While sensitivity analysis and ER axiom-based validation were conducted to enhance robustness, future research could explore hybrid renewable energy systems (wind-solar systems), integrate more detailed techno-economic and life-cycle assessments using harmonised site-specific datasets, and compare the proposed AHP–ER framework with other uncertainty-handling MCDM methods.

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Abbreviations

The following abbreviations are used in this manuscript:

MCDM	Multi-Criteria Decision-Making
AHP	Analytic Hierarchy Process
ER	Evidential Reasoning
LCOE	Levelised Cost of Electricity (US$/kWh)
LCOH	Levelised Cost of Hydrogen (US$/kg H_2)

PBP	Payback Period (year)
FID	Final Investment Decision
SWHPS	Solar–Wind Hybrid Power Station
GIS	Geographic Information Systems
MODM	Multi-Objective Decision-Making
MADM	Multi-Attribute Decision-Making
a_{ij}	Represents the relative importance of criterion i over criterion j
CR	Consistency Ratio
CI	Consistency Index
λ_{max}	Maximum eigenvalue of the matrix
n	Number of criteria
RI	Random Index
H_n	nth evaluation grade used to assess the main and sub-criteria
e_i	ith sub-criteria
$\beta_{n,i}$	Belief degrees of the sub-criteria e_i
$S(e_i)$	Distributed assessment
$m_{n,i}$	Basic probability masses of the sub-criteria e_i assessed to H_n
ω_i	Weight of the ith sub-criteria
$m_{H,i}$	Remaining probability not distributed among the individual grades after evaluating all grades
β_n	Combined belief degrees
β_H	Belief degree unassigned to any individual grade considering all criteria
$U(H_n)$	Estimated utility value corresponding to evaluation grade H_n
IDS	Intelligent Decision System
WS	Wind Speed
O&M	Operations and Maintenance

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