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Article

Powering the Green Transition in Quad-Sectors with Hybrid Clean Energy Technologies

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Abstract

Hybrid renewable energy systems (HRESs) represent a promising strategy for reducing carbon emissions across multiple sectors by integrating complementary resources such as solar, wind, hydropower, and energy storage technologies. Identifying the most suitable location for a pilot installation requires a comprehensive evaluation that balances technical performance, environmental benefits, social considerations, and economic feasibility. This study employs an enhanced multi-criteria decision analysis (MCDA) framework, supported by machine learning (ML) techniques, to assess four pilot sites developed within the HY4RES project: a rural community, an aquaculture facility, a port installation, and an agriculture network. A comprehensive set of key performance indicators (KPIs) was established to capture technical, environmental, social, and economic dimensions. These include the degree of hybridization, carbon intensity, community benefit scores, net present value, levelized cost of energy, and payback period. After collecting and normalizing the site-specific data, ML EL-SVM, decision tree, and logistic regression models as computational surrogates designed to bypass the multi-step, matrix inversion mathematical requirements of the AHP when screening massive numbers of future scenario outputs supporting consistency checks and sensitivity exploration were used, along with criterion adjustments, to refine the relative importance of each KPI. The Analytical Hierarchy Process (AHP) was employed to assess potential factors and rank the sites, with the rural site achieving the highest overall score in the system, driven by its complex four-source hybrid configuration and strong community-level benefits. The agriculture scheme ranked second, demonstrating significant potential for carbon emission reductions. The port pilot placed third, distinguished by high technical innovation but more limited social impact. The aquaculture site ranked fourth, primarily due to environmental scores, despite its economic self-sufficiency.

Keywords: renewable energy solutions; green transition; industry and communities; MCDA; AHP; ML; hybrid energy systems

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1. Introduction

Global energy systems are undergoing rapid change, yet the underlying drivers of demand growth and the persistence of fossil-based generation continue to challenge climate objectives. The International Energy Agency reports that global energy demand increased by 2.2% in 2024, exceeding the average growth rate of the previous decade [1]. In the power sector, Ember reports that fossil generation accounted for 59.1% of global electricity generation in 2024, indicating that deep decarbonization of the electricity supply remains unfinished [2]. At the same time, the impacts and risks associated with climate change have become increasingly evident, and the IPCC AR6 Synthesis Report emphasizes the urgency of near-term mitigation to limit escalating risks [3]. In Europe, this urgency is reflected in binding policy targets, including the European Climate Law, which sets the framework for achieving climate neutrality by 2050 [4].

Hybrid renewable energy systems integrate multiple renewable sources and, where relevant, storage and advanced control to improve reliability, self-sufficiency, and emissions performance under variable resources and loads. Within the HY4RES research line, hybrid solutions are positioned as a pathway for small energy communities and sector-specific applications to increase renewable penetration while balancing technical feasibility, environmental outcomes, social value, and economic performance [5]. This multi-dimensional nature of hybrid system deployment implies that single-criterion decision rules are insufficient for selecting among competing project options, particularly when pilots span different sectors with distinct operational constraints.

The HY4RES project, funded under the Interreg Atlantic Area program, addresses this challenge by developing and evaluating micro-scale hybrid solutions in four sectors: rural communities, aquaculture, ports, and irrigated agriculture [6]. A recent study used machine learning and renewable energy by exploring solar and wind energy solutions for a sustainable future, including innovations in energy storage [7]. Data-informed hybrid renewable system design based on building energy demand prediction used a machine learning and deep learning approach, and a recent study developed optimization algorithms with machine learning in modeling approaches to hybrid energy balance to improve ports' efficiency [8,9]. A hybrid energy solution to improve irrigation systems was presented with optimization model comparison [10]. For each pilot domain, HY4RES combines site-specific data collection with modeling and scenario evaluation to assess technical performance and potential benefits. Complementary technical studies support this sectoral evaluation, including port energy balance modeling and forecasting approaches [11], irrigation hybrid optimization comparisons, aquaculture hybrid energy management assessments [12,13], and small energy communities [14]. However, while each pilot can be evaluated within its own sectoral context, prioritizing deployment or demonstration pathways across the portfolio requires a consistent cross-sector decision framework. Multi-criteria decision analysis provides a structured approach for comparing complex alternatives across multiple, potentially conflicting objectives. In HY4RES coursework documentation with supervision and monitoring of this research work, an AHP-style MCDA framework is implemented to compare four candidate pilots using harmonized key performance indicators and explicit criterion weights [13]. The framework draws on the project's economic and KPI datasets that consolidate NPV, LCOE, payback, carbon intensity, social scoring, and hybridization indicators for cross-site comparison. The relevance of multi-criteria evaluation and robustness testing for hybrid renewable solutions is further supported by HY4RES-aligned work on multi-criteria decision-making and sensitivity analysis in small community hybrid systems. Conversely, refs. [14–18] advance decision support scholarship by examining emerging multi-criteria decision-making (MCDM) approaches in renewable energy planning. The study highlights deficiencies in stakeholder engagement and introduces

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participatory frameworks employing the AHP and PROMETHEE. Refs. [18,19] conduct an assessment of policy pathways aimed at enhancing RES-E penetration in Greece, applying MCDM techniques to compare alternative scenarios on the basis of economic cost, emissions performance, and societal acceptance. In [20], the authors propose an integrated sustainability and resilience indicator system for local-scale energy technologies, combining MCDM with a structured set of KPIs spanning environmental, economic, and social domains. Ref. [21] utilize MCDM to support site selection for wave energy installations in Vietnam, evaluating locations according to wave resource availability, ecological considerations, and grid accessibility. Furthermore, ref. [22] offer a foundational review of MCDM applications in sustainable energy planning, covering methodologies such as the AHP and fuzzy-based models, and underscoring their capacity to reconcile competing performance indicators. Finally, ref. [23] provide comprehensive reviews of decision-making processes in renewable energy investments, emphasizing the integration of MCDM with financial metrics (NPV, IRR) and environmental indicators to strengthen project appraisal.

Accordingly, the central aim of the present research is to formulate an MCDM-based model [24] tailored to hybrid renewable energy systems in small communities, incorporating clearly defined key performance indicators and a rigorous sensitivity analysis. A new study proposes a systematic approach to solving problems using multi-criteria decision-making (MCDM) techniques, where a framework was presented that integrates the criteria of AI methods [25].

Hence, the objectives of this research are: (i) compile and present a KPI evidence base used for four-site cross-comparison, (ii) implement an MCDA weighting and scoring procedure to derive a transparent ranking, (iii) test ranking robustness through sensitivity analysis, and (iv) after collecting and normalizing the site-specific data, ML-based feature weighting and pattern detection methods are applied together with criteria-driven adjustments to refine the relative importance of each KPI. Hereafter, the study core highlights that traditional MCDA/AHP studies focus on macro-policy, regional planning, or uniform single-asset site selection. A significant research gap exists in evaluating the portfolios of heterogeneous, micro-scale hybrid renewable energy systems across distinct sectors. This study bridges the gap by coupling traditional MCDA with machine learning algorithms like Efficient Linear SVMs. Instead of relying on static comparisons, ML acts as a surrogate classifier to validate AHP model consistency and analyze patterns. The development framework provides a transferable decision pathway tested across four real-world "Quad-Sectors," balancing public values with industrial efficiency.

So, the purpose of this research work can be summarized as follows: (i) The research starts with Section 1. An introduction that sets the context for assessing hybrid renewable energy systems across different sectors. It outlines the relevance of integrating multiple renewable technologies and the need for a structured decision-making approach to compare diverse sites and applications. (ii) Section 2. The methodology section forms the core of the work. It first presents the concept of hybrid renewable energy systems for sectoral applications, explaining how different combinations of technologies can meet varying energy demands. This is followed by detailed site descriptions, covering four distinct contexts: a rural site, a port site, an agriculture site, and an aquaculture site. Each site is characterized in terms of its energy needs, environmental conditions, and operational constraints. The study then introduces the decision frameworks used to evaluate the systems, establishing the criteria and structure for multi-criteria decision analysis. A dedicated subsection on financial modeling explains how net present value (NPV) and levelized cost of energy (LCOE) are formulated to assess economic performance. The methodology continues with the normalization and scoring procedures that allow different indicators to be compared on a common scale, followed by the development of a key performance indicator (KPI) framework to integrate technical, economic, and environmental metrics. Finally, the section describes the machine learning application, which supports pattern recognition, prediction, and optimization within the decision process. (iii) Section 3. Results and Discussion present the outcomes of the analysis. A comparative analytical framework to understand how different hybrid systems perform across the four sustainability dimensions and how local characteristics influence feasibility and transferability is presented. It initiates with the normalization and weighting results, showing how the criteria were balanced and how each site performed across indicators. This leads to the overall multi-criteria decision analysis (MCDA) scores and ranking, where the hybrid system configurations are compared and ordered according to their aggregated performance. The Discussion analyzes these findings in depth, starting with the interpretation of the rankings, then examining why the rural site emerges as a relevant option, and finally exploring the comparison between the agriculture and port sites, particularly how impact-driven scaling influences their relative positions. It continues by examining trade-offs and uncertainties, exploring how different dimensions influence the evaluation of hybrid renewable energy systems. This includes the balance between economic and non-economic value, the nuances of environmental performance, and the social, governance, and technical uncertainties that shape decision-making in complex energy projects. The analysis then moves to the sensitivity analysis results, showing how variations in assumptions or criteria weights affect the overall rankings and robustness of the conclusions. This is followed by a reflection on the methodological limitations, acknowledging constraints in data, modeling choices, and the generalizability of the findings. (iv) The work is completed with Section 4. Conclusion, which synthesizes the study's outcomes. It highlights the key insights gained from the multi-criteria assessment and machine learning analysis and emphasizes the relevance of the results for decision-making, particularly in guiding stakeholders toward more informed, resilient, and context-appropriate renewable energy strategies.

2. Materials and Methods

2.1. Hybrid Renewable Energy for Sectoral Decarbonization

Hybrid renewable energy systems integrate multiple renewable sources and, where applicable, storage and advanced control to improve reliability, autonomy, and emissions performance under variable resources and loads. The HY4RES project, funded under the Interreg Atlantic Area program, develops and evaluates micro-scale hybrid renewable solutions for four target sectors: rural communities, ports, agriculture, and aquaculture [6]. In the HY4RES research context, hybrid energy communities are assessed through multi-dimensional performance indicators and comparative evaluation of solution configurations [5]. The sectoral motivation is that different applications face different operational constraints, such that a single metric rarely determines the best design. Accordingly, hybrid system studies emphasize simultaneous consideration of technical operation, economics, environmental performance, and social outcomes. The project combines site-specific data collection with modeling-based evaluation to support pilot development and comparison. In parallel, project economic and KPI datasets provide harmonized indicators to enable cross-sector assessment. A methodology structure aligns with strengths in technical communication and optimization modeling as follows (Figure 1): (i) the integration logic between PV, wind, hydro, PAT, and BESS; (ii) the multi-objective nature of the evaluation with multi-criteria and machine learning (ML) analyses of EL-SVM, decision tree, and logistic regression models as computational surrogates designed to bypass the multi-step, matrix inversion mathematical requirements of the AHP when screening massive numbers of future scenario outputs supporting consistency checks and sensitivity exploration; (iii) the comparative dimension (industry vs. community); and (iv) the decision-making and ML pathway from raw data to optimal solutions. This flowchart presents a continuous, end-to-end decision framework for identifying and selecting the most suitable energy system configuration for a given site. It begins by situating the problem within specific sectors—such as rural areas, ports, agriculture, and aquaculture—and then characterizes each site according to scale, demand, resilience needs, prioritizations, and broader decision drivers. From there, the process moves into parameterization, integrating diverse input data including hydro, photovoltaic, wind, and battery capacity information. These inputs feed into a detailed characterization of consumption patterns, battery charging and discharging behavior, and buy/sell dynamics, followed by a decision on whether hybridization of energy sources is appropriate. Only accepted operational cycles proceed to the next stage, where potential energy availability is assessed, and system constraints are established. Once the technical foundation is set, the workflow transitions into a strategic evaluation phase that combines quantitative techno-economic, social, and environmental assessments. Financial modeling is performed alongside data normalization and scoring procedures. Key performance indicators are normalized and weighted, and criteria weighting is refined using methods such as the Analytic Hierarchy Process, ensuring consistency across decision factors. Sensitivity analysis tests the robustness of the evaluation under varying assumptions. These elements converge into an overall score that feeds into a results and analysis stage, followed by a structured discussion. A final acceptance decision determines whether the proposed configuration qualifies as the "best solution," completing the decision-making loop.

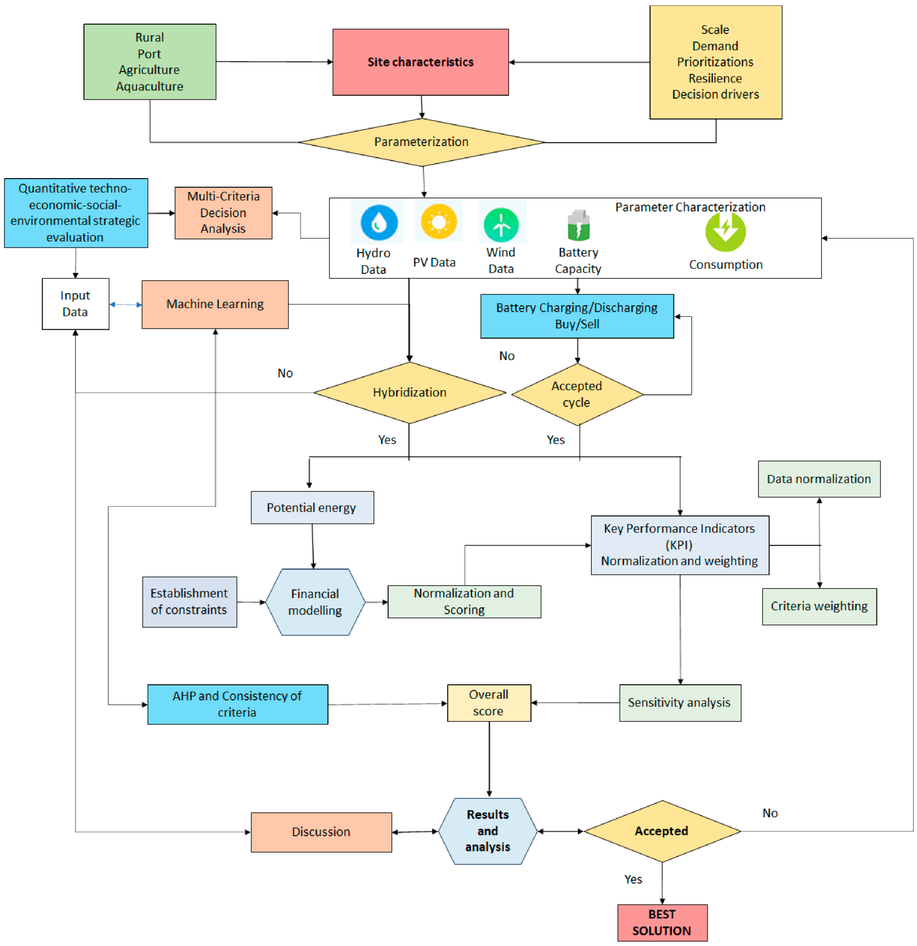

Figure 1. Flowchart methodology of hybrid renewable energy for sectoral decarbonization.

2.2. Site Descriptions

This research examines four different hybrid energy pilot sites corresponding to the HY4RES project target sectors. Each site's context and key characteristics are summarized as follows.

2.2.1. Rural Site

The rural pilot site is centered on an old watermill, located on the Sousa River in northern Portugal. The site features an existing hydraulic infrastructure providing a usable head of about 2.8 m. The surrounding area is a small rural community, which is currently connected to the public grid. The intervention also creates value for the mill owners through asset revitalization, supports rural tourism by enhancing the site as a demonstrator and educational point of interest, and provides a concrete reference case for private individuals and small communities interested in energy autonomy. In this sense, the social impact is indirect and geographically wider, because the pilot functions as a replicable archetype and a visibility asset rather than only a local supply upgrade. The hybrid system proposed for this site converts the watermill to micro hydropower while adding complementary solar PV, wind, and battery storage to form a local microgrid. The goal is to supply a significant portion of the local load with renewable energy, increasing self-sufficiency and providing a demonstrator for rural clean energy transition [5].

Favorable local conditions support this concept. The site is characterized by high water availability throughout the year, and the local context also supports integration with other renewable energy sources. Equally important, the historical and cultural value of the site is emphasized in the project documentation as a factor that can enhance visibility and stakeholder support. In summary, the rural site represents a community-scale hybrid microgrid, emphasizing sustainability, heritage restoration, and community development. Its scale is the smallest of the four analyzed sites, and it is not primarily profit-driven. Any excess power could be injected into the grid, but the main aim is local self-reliance and demonstration.

Key technical components are defined through scenario-based sizing and optimization in the rural site work, where solar PV and wind capacities are varied within feasible ranges, while hydropower capacity is treated as fixed, and storage is used to support balancing and reduce grid dependence.

2.2.2. Port Site

The port pilot is located in Asturias, northern Spain. The pilot installation is a hybrid module integrating wind, solar, tidal, and hydrokinetic generation, and a pump as turbine-based storage. The implementation is described as a micro-scale demonstrator, not intended to power the entire port, but designed to test multi-source integration and management strategies under real operating conditions [11]. Associated work emphasizes modeling, optimization, and forecasting-oriented management approaches for improving operational performance and efficiency.

This site exemplifies technical novelty and integration complexity, and it aligns with policy and sectoral goals for port decarbonization and smart infrastructure development. Because of the demonstrator scale and bespoke nature, direct energy revenue is not expected to be the dominant value driver. Instead, much of its value lies in demonstration, learning, and replicability potential across similar port environments [11]. Socially, benefits are concentrated within port operations and associated stakeholders, with more limited direct community-wide impacts compared with the rural site. Environmentally, the module supports decarbonization of specific end uses and provides an applied platform for validating multi-resource operation with storage in a maritime setting.

2.2.3. Agriculture Site

The irrigation pilot is located in Spain [12]. The irrigation network operates with substantial pumping demand during the irrigation season and relies on electrical energy to deliver pressurized water through the distribution system. The hybrid solution assessed consists of a solar PV system combined with pumped storage using a pump as turbine operation and the existing water infrastructure, enabling surplus solar electricity to be stored via pumping and recovered when solar availability is low. The irrigation case is characterized by a large scale relative to the other pilots, meaning that absolute impacts on electricity use and emissions can be substantial. Socially, benefits accrue primarily to the irrigation association and farmers through reduced pumping costs and improved energy resilience [12]. Technically, the main elements are mature, but the scale and integration with water operations remain a significant engineering and operational challenge.

2.2.4. Aquaculture Site

The aquaculture pilot site is an energy system serving a fish processing and aquaculture facility in Ireland, and it comprises two interconnected locations: a primary site housing processing plants and a secondary site where a small hydropower plant on a nearby river is already installed. The documented configuration includes wind generation at the primary site and run-of-river hydropower at the secondary site, with the grid covering any shortfall and backup generation historically used for critical processes. Under the HY4RES scope, additional components were assessed, including solar PV and an operational biomass concept that uses surplus renewable electricity to support a wood drying unit, effectively converting excess electricity into a useful product and introducing a flexible load that can be scheduled when surplus occurs.

The energy demands at fish processing plants are complex, including large refrigeration loads, cleaning and hot water needs, and process equipment that can cause high variability and peaks in demand [26]. Improving self-sufficiency and reducing electricity costs, as well as emissions, are major drivers. Its notable features include a multi-source hybrid system and an additional flexible demand concept intended to improve economic performance by using surplus generation more productively.

The site is grid-connected in the main scenarios, meaning selling excess and drawing shortfalls from the grid are possible in most modeled cases [13]. Socially, the site supports local employment in a rural coastal community, but the primary beneficiaries are the operating company, implying a moderate social score relative to a community microgrid. Environmentally, it has a certain carbon reduction potential by increasing renewable supply relative to grid consumption and by reducing curtailment through flexible use of surplus.

2.3. *The Decision Frameworks*

To provide a robust answer to the research question, this study employs a dual-methodological framework: a quantitative and qualitative strategic evaluation using multi-criteria decision analysis (MCDA) and forecast estimation using ML. This approach is designed specifically to resolve the conflict between financial efficiency and strategic value in decentralized energy systems.

The evaluation problem is structured as a hierarchical decision matrix. This structure allows for the decomposition of the complex "viability" question into measurable components. (i) Level 1 (Goal): Select the pilot site that maximizes the strategic objectives of the HY4RES consortium (innovation and resilience); (ii) Level 2 (Criteria): Four competing dimensions were selected: technical, environmental, social, and economic. These criteria represent the Triple Bottom Line of sustainability, plus a technical dimension essential for research pilots; and (iii) Level 3 (Types): Four different pilot sites (rural, port, agriculture, and aquaculture).

2.3.1. Social Scoring Rubric and Operational Definitions

To standardize the qualitative assessment across heterogeneous pilot environments (ranging from community to private industrial operations), a standardized social benefit score (SBS) was implemented. The social criteria evaluate three primary sub-dimensions: Community Visibility and Replicability Narrative, Local Stakeholder Economic/Employment Stabilization, and Educational/Public Engagement Value (Table 1).

Table 1. Social scoring rubric matrix.

Score Range	Classification	Empirical Siting Operational Rubric/Criteria Checklist
0.81–1.00	Broad Public/ Community Flagship	System delivers direct public-facing value, restores regional cultural/historical heritage, provides open educational access, and serves as an archetype microgrid with high community-wide acceptance.
0.51–0.80	Localized/Collective Associative Benefit	Benefits accrue directly to collective sector associations, cooperatives, or local farming networks. Medium-to-high visibility within regional industry clusters; indirect job stabilization.
0.21–0.50	Concentrated/Private Infrastructure Value	Benefits are largely internalized within single commercial operating companies or localized site infrastructure. Social impact is bounded by private operations, with localized employment maintenance.
0.00–0.20	Negligible Societal Spillover	Strictly restricted access; system yields no measurable regional community value, public awareness, or local socioeconomic interaction.

2.3.2. Evaluator Panel Methodology and Expert Selection

The initial assignment of pairwise qualitative assessments and baseline scores was carried out under the framework of the HY4RES project coursework documentation and technical monitoring. To eliminate subjective bias and ensure data alignment, a multidisciplinary panel of nine evaluators was selected across three primary sectors:

(i) Academic Researchers and Engineering Supervisors (n = 3): Specializing in multi-criteria decision models and hybrid energy microgrids.
(ii) Site Operators and Technical Managers (n = 3): Representing the direct operational realities of the four distinct sectors (rural, port, agriculture, aquaculture).
(iii) Regional Public Authority/Policy Liaisons (n = 3): Ensuring alignment with local development frameworks and Interreg Atlantic Area program guidelines.

2.3.3. Stakeholder Survey and Data Collection Process

The survey and qualitative-to-quantitative transformation workflow followed a three-phase procedure:

(i) **Survey Instrument Sizing:** Structured questionnaires were delivered to target stakeholder groups at each site (e.g., local mill community neighbors in Portugal, port operators in Asturias, irrigation association members in Spain, and processing plant managers in Ireland).
(ii) **Questionnaire Attributes:** Questions mapped to operational metrics on a Likert scale (1–5) measuring: perceived environmental safety, expected regional economic benefit, willingness to cooperate with the infrastructure, and local asset revitalization value.

(iii) **Data Aggregation and Consistency Checks:** The responses were normalized into the final qualitative index interval [0, 1]. These values were subsequently subjected to programmatic validation via the **Efficient Linear Support Vector Machine (EL-SVM)** model. EL-SVM operated as a fast surrogate classifier to systematically test consistency checks, mapping the 16-dimensional vector inputs across technical, environmental, social, and economic parameters to ensure mathematical robustness against expert subjectivity.

2.4. Financial Modeling

To establish a baseline for comparison, standard industry metrics were calculated using the operational data collected. These metrics serve as the control variable, representing the pure market viability of each pilot, absent a subsidy or strategic value.

2.4.1. Net Present Value (NPV)

The NPV quantifies the total financial value of the pilot over its lifetime (20 years). It serves as a boundary condition for investment decisions. It is defined as the sum of incoming and outgoing cash flows, discounted to the present value to account for the time value of money:

$$NPV = -C_0 + \sum(t = 1 \; to \; n) \, [\, (R_t - (O\&M_t + R_{ep,\,t})) \, / \, (1 + r)^t] \tag{1}$$

where C_0 is the Initial Capital Expenditure (*CAPEX*); R_t is the Annual Revenue (or savings from avoided grid electricity purchases); *O&Mt*: Operations and Maintenance costs; *r* is the discount rate (assumed 4% for social infrastructure, reflecting public sector risk profiles); and *n* is the project lifetime (20 years).

2.4.2. Levelized Cost of Energy (*LCOE*)

While the *NPV* measures the total value, the *LCOE* represents the average cost to generate 1 kWh of electricity. Then, the *LCOE* can be calculated by first taking the net present value of the total cost of building and operating the power-generating asset. This number is then divided by the total electricity generation over its lifetime. This metric allows for a fair comparison of generation efficiency across different scales (e.g., comparing a 7.5 kW rural turbine vs. a 1.2 MW industrial wind turbine) by normalizing costs against energy output:

$$LCOE = [\sum(t = 1 \; to \; n) \, (C_0 + O\&M_t) \, / \, (1 + r)^t \,] \, / \, [\sum(t = 1 \; to \; n) \, E_t / \, (1 + r)^t] \tag{2}$$

where E_t is the total energy generated in year t (kWh).

2.5. Normalization and Scoring

Since the criteria have heterogeneous units (Euros, $kgCO_2$, qualitative scores), all values were normalized to a dimensionless scale [0, 1] using Linear Sum Normalization:

$$S_{ij} = x_{ij} / \sum(i = 1 \; to \; m) \, x_{ij} \tag{3}$$

where S_{ij} is the normalized score of pilot i under criterion j. The Final Preference Index (PI) for each pilot was calculated using the Weighted Sum Model:

$$PI_i = \sum(j = 1 \; to \; k) \, w_j \cdot S_{ij} \tag{4}$$

This index provides a single scalar value representing the "Strategic Utility" of each pilot.

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2.6. KPI Framework

To evaluate the pilot sites on a common basis, a set of key performance indicators (KPIs) was defined spanning four main categories: technical, environmental, social, and economic. Table 2 summarizes the KPI set used in this report, including the unit and the direction of preference.

Table 2. KPI framework used for cross-site comparison and MCDA.

Category	KPI	Unit	Preference	Notes
Technical	Degree of hybridization	Count	Higher better	Count of distinct sources and storage elements
Environmental	Carbon intensity	kg CO_2/kWh	Lower better	Operational intensity in HY4RES datasets
Social	Social benefit score	0 to 1	Higher better	Qualitative score assigned in the project process
Economic	Net present value (NPV)	EUR	Higher better	Computed from discounted cash flows
	Levelized cost of energy (LCOE)	EUR/kWh	Lower better	Computed over the project life cycle
	Payback period	Years	Lower better	Based on cumulative savings versus investment

Table 3 reports the raw KPI values used as inputs for the subsequent normalization and AHP-based scoring. The values are taken from the HY4RES project and KPI datasets used for the MCDA. The social scoring framework evaluates social performance based on stakeholder engagement, the identification of primary beneficiaries, and local geographic contexts. For instance, distinguish why a community microgrid (like the rural site) scores a perfect 1.00 due to its widespread public value, rural tourism, and educational visibility, whereas industrial or corporate pilots (like aquaculture) score lower because benefits remain concentrated within the operating company.

Table 3. Raw KPI values used for MCDA inputs.

Site	NPV (€)	LCOE (€/kWh)	Payback (y)	Carbon Intensity (kg CO_2/kWh)	Social Score	Hybridization
Rural	89,947	0.146	6.0	4.0	1	4
Port	1,618,342	0.104	7.0	5.0	0.4	5
Agriculture	7,064,364	0.021	2.0	10.0	0.8	2
Aquaculture (Ireland)	26,332,800	0.058	2.0	8.5	0.6	3

Figure 2 reveals the distinct performance profiles across the four site types. Aquaculture leads economically, with the highest NPV (€26.3 M), low LCOE (0.058 €/kWh), and the shortest payback period (2 years), making it the most financially attractive option. Agriculture also shows strong economic indicators, with a high NPV (€7.06 M) and the lowest LCOE (0.021 €/kWh), though its carbon intensity is the highest (10 kgCO_2/kWh), which may raise environmental concerns in equipment manufacture. The port site offers moderate economic returns (NPV €1.62 M) and a balanced carbon intensity (5 kgCO_2/kWh), but its social score is the lowest (0.40), suggesting limited societal benefits, more focused on the port infrastructure. In contrast, the rural site, while having the lowest NPV (€89.9 K), achieves the highest social score (1.00) and lowest carbon intensity (4 kgCO_2/kWh), indicating strong social and environmental performance despite limited financial viability. These results highlight trade-offs between economic, environmental, and social dimensions, with aquaculture and agriculture favoring profitability, and rural emphasizing sustainability and community impact.

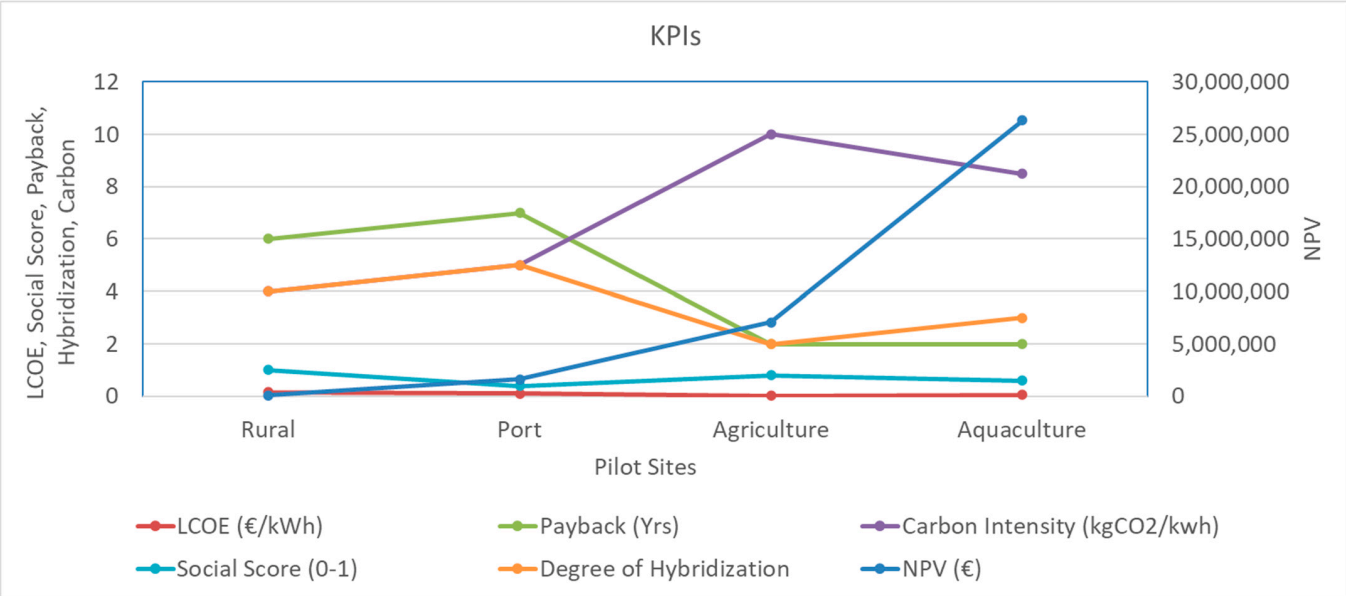

Figure 2. Key performance indicators adopted.

2.7. Machine Learning Algorithm

The purpose of applying the machine learning (ML) algorithm was to identify the optimal pilot site from a set of four candidate types (rural, port, agriculture, or aquaculture), based on the highest calculated value of the Analytical Hierarchy Process (AHP) ranking index. Using the AHP Index as the definitive criterion, the pilot sites were ranked from first to fourth place. The role of the ML model was to classify and thus select the top-ranked site. For this analysis, a total of sixteen predictor variables were considered, with the pilot site classification serving as the response variable, as detailed in Table 4.

Table 4. Configuration of the predictors–response for the ML model.

Predictors	Response
1—Rural (Technical) 2—Port (Technical) 3—Agriculture (Technical) 4—Aquaculture (Technical) 5—Rural (Environmental) 6—Port (Environmental) 7—Agriculture (Environmental) 8—Aquaculture (Environmental) 9—Rural (Social) 10—Port (Social) 11—Agriculture (Social) 12—Aqua (Social) 13—Rural (Economic) 14—Port (Economic) 15—Agriculture (Economic) 16—Aquaculture (Economic)	Best AHP ranking of pilot site (rural, port, agriculture, or aquaculture) of a series of scenarios or for each scenario individually

This research employed three machine learning (ML) models, described as follows:

- Efficient Linear Support Vector Machine (EL-SVM): The model used a support vector machine (SVM) as the learner, with both the solver and regularization set to auto. The regularization strength was also set to auto, with a relative coefficient tolerance of 0.0001.
- Decision Tree (DT): This ML method was configured using a medium tree preset, with a maximum number of splits of 20. The Gini diversity index was used as the split criterion, and surrogate decision splits were disabled.
- Efficient Logistic Regression (ELR): This model employed logistic regression as the learner. Like the EL-SVM configuration, both the solver and the regularization parameters were automatically determined by the algorithm. The regularization strength was also set to auto, and the relative coefficient tolerance was fixed at 0.0001.

The performance of the ML models was evaluated using the following metrics.

- The F1-score was calculated for all ML models considering the four classes (i.e., each pilot site).

$$F1 = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{Precision + Recall} \tag{5}$$

- The macro-F1 was evaluated considering an equal weight for each class, as follows:

$$Macro\text{-}F1 = \frac{\sum_{i=1}^{n} F1_i}{n} \tag{6}$$

where n is the number of classes (or pilot sites in this case).

The dataset partitioning was modeled using a fixed random generator state, in which its division was performed randomly for each scenario without applying any clustering or stratification procedures. It was implemented using MATLAB R2024b, considering the function "rng(42,'twister')". Particularly, the Classification Learner APP was employed in this research. The performance metrics are calculated for the entire dataset to observe an overall accuracy. Consequently, the matrix confusion contains all points of the dataset for all pilot sites. For all ML methods, a 5-fold cross-validation scheme was implemented. This approach was adopted because the dataset is limited in size, making it suitable for ensuring robust training and evaluation of the ML models.

An Efficient Linear Support Vector Machine (EL-SVM) was selected due to its computational efficiency and its suitability for small, structured datasets. EL-SVM, decision tree, and logistic regression models as computational surrogates are designed to bypass the multi-step, matrix inversion mathematical requirements of the AHP when screening massive numbers of future scenario outputs, supporting consistency checks and sensitivity exploration. The performance metrics obtained in the results indicate that this model achieved the best classification performance for the dataset. The model was implemented in MATLAB R2024b using the BFGS optimization solver, which is well-suited for convex problems such as linear EL-SVMs. A ridge regularization penalty was applied to control model complexity and avoid overfitting. The regularization parameter λ was set to $1/n$, where n is the number of scenarios, and this value was confirmed through cross-validation to provide the best balance between bias and variance for the dataset size. The optimization process terminated when the relative change in the coefficient vector (beta tolerance) fell below 0.0001, ensuring numerical convergence. Because the classification task involves four pilot site categories, a one-versus-one coding strategy was used to construct the multiclass classifier from multiple binary EL-SVMs.

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The EL-SVM solves the regularized optimization employing the efficient algorithm for linear kernels, as follows:

$$\min \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n}(\xi_i + \xi_i^*) \quad (7)$$

which depends on $y_i(wx_i + b) > 1 - \xi_i$, where w corresponds to the weight vector, b is the bias term, x_i is the i-th training observation, y_i corresponds to the categorial predicted variable, ξ_i and ξ_i^* are the slack variables, and C is the regularization parameter.

The EL-SVM model was not intended to discover an external "ground truth" optimum, but rather to learn a surrogate representation of the AHP-based decision rule. The purpose of the model is therefore to provide a fast, lightweight classifier that can be embedded in Simulink for scenario exploration and real-time decision support, rather than to independently validate the MCDA outcome. The ML model is explicitly utilized as a fast, lightweight surrogate classifier trained to reproduce and learn the complex underlying decision rules of the AHP-based ranking.

3. Results and Discussion

3.1. Normalization and Weighting

The KPI values have different units and scales. To feed them into a unified MCDA model, the normalization of each indicator is necessary on a dimensionless scale (Figure 3). Typically, a 0–1 scale is used where 1 is the best-performing alternative on that indicator and 0 the worst, or vice versa for cost type indicators [18]:

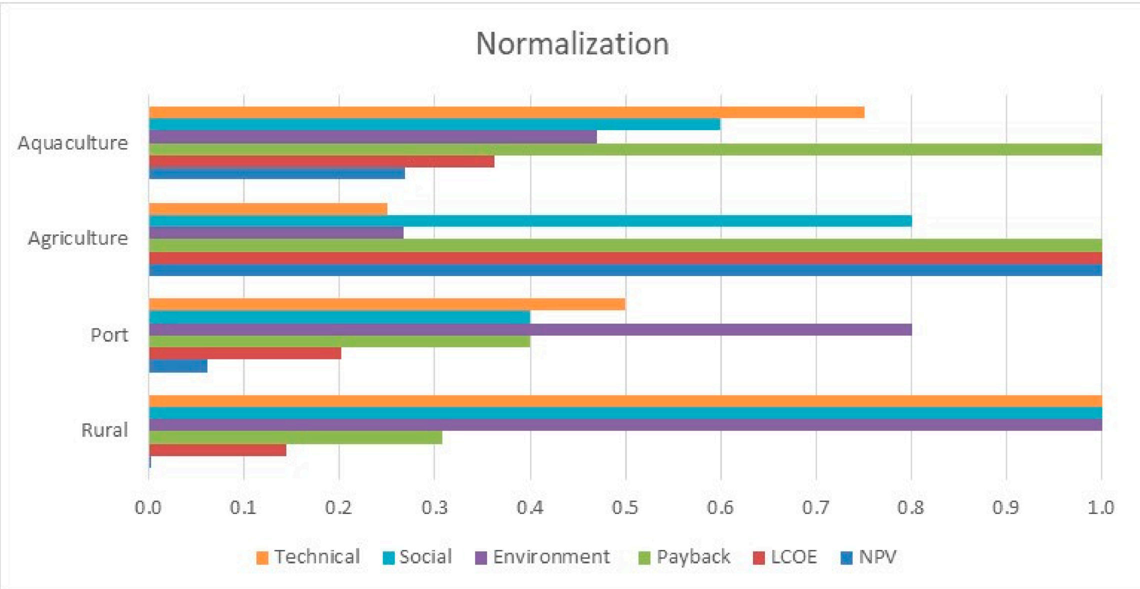


Figure 3. Normalization of each dimension.

For indicators where a higher value is better (also called benefit criteria), the normalization of each site value to the range [0; 1] is performed by dividing by the maximum value among the four sites [18]. For indicators where a lower value is better, an inverse normalization is used.

MCDA–AHP requires weighting each criterion to reflect its relative importance. In this research, weights were determined through the project process and aligned with HY4RES objectives, which emphasize technical demonstration and environmental performance alongside social outcomes, while treating pure financial return as less decisive in a publicly funded pilot context. Specifically, the weights used were: (i) technical: 35% of overall decision weight; (ii) environmental: 30% weight; (iii) social: 25% weight; and (iv) economic: 10% weight. In this research, there are multi-pilot installations financed through a public innovation program (Interreg Atlantic Area), and the primary objectives are focused on technical integration novelty, community-wide social scaling, and environmental decarbonization. Therefore, the expert framework intentionally treats immediate financial return (NPV/LCOE) as less decisive, since structural economic weaknesses in micro-scale pilots are acceptable if public value, replication data, and institutional learning are maximized.

This weighting scheme sums to 100% and reflects a strategic choice: prioritize technical viability and innovation and environmental impact, ensure social considerations are significant, and accept that economic return is the least critical given the pilots' demonstration nature [6]. The weights were validated via an AHP pairwise comparison exercise among the criteria, consistent with standard AHP practice, and the decision process retained the resulting weights for the analysis.

After normalizing individual indicators, as grouped criteria (technical, environmental, social, economic), sub-indicators within each criterion are aggregated in Figure 4:

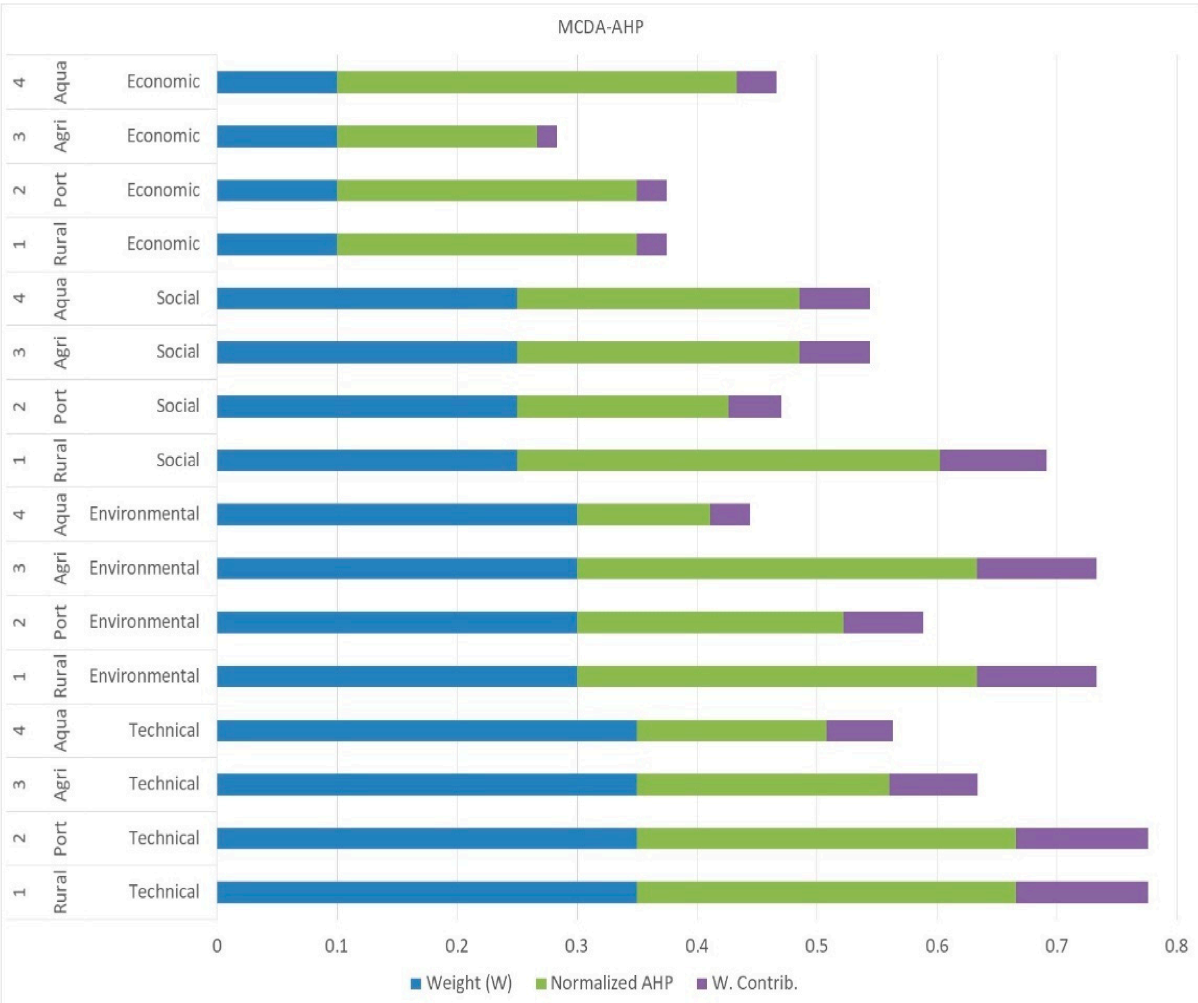


Figure 4. Weight emphasizing technical and environmental performance alongside social and economic outcomes.

Technical: The degree of hybridization is used as a raw measure, normalized by the maximum value. In addition, the technical criterion scoring in the AHP incorporates the project's emphasis on integration novelty, particularly in a demonstrator context [9,11].

Environmental: The primary indicator was carbon intensity (or effectively renewable fraction). The normalization of carbon intensity is performed using the minimum divided by the actual, so lower CO_2 corresponds to a higher normalized score.

Social: The social score is already between 0 and 1 for each site in the dataset, and these values are used as the basis for social performance. The interpretation of social performance is supported by the site visits, which specify the principal beneficiaries and stakeholder context for each pilot. The rationale used to normalize the social scores includes qualitative impact levels and the evaluation process based on expert judgment, consortium discussions, site documentation, and stakeholder-oriented assessment within HY4RES. The social criterion was comparatively assessed across the four pilots, considering their different sectoral contexts and beneficiary structures. Therefore, the MCDA results should be interpreted as context-dependent and intended for project-specific demonstrator prioritization rather than as a universally transferable ranking.

Economic: Three sub-indicators (NPV, LCOE, payback); rather than assigning arbitrary weights to each, they are qualitatively examined for overall economic attractiveness. In practice, because all three measures contain related information (projects with high NPV often also show low LCOE and short payback in the same dataset), a simplified procedure is used by using the combined interpretation as recorded in the project scoring sheets. This is one area where expert judgment from the project process is reflected directly in the within-criterion scoring used.

The outcome of normalization is captured in Table 5, where normalized scores for each criterion at each site are shown. These serve as the basis for the MCDA ranking once the criterion weights are taken into account. Scores are then normalized and performance is shared within each criterion (summing to 1 across sites). A higher score is better.

Table 5. Normalized criterion scores for each site, with criteria weights.

Criterion	Weight (W)	Rural	Port	Agriculture	Aquaculture
Technical	0.35	0.316	0.316	0.211	0.158
Environmental	0.30	0.333	0.222	0.333	0.111
Social	0.25	0.353	0.176	0.235	0.235
Economic	0.10	0.250	0.250	0.167	0.333

Once the criterion weights and criterion level priority vectors are defined, the overall priority for each site is calculated as a weighted sum, that is, the dot product of the criterion weights with the site scores across the four criteria. For site i, the overall score Si is

$$S_{\mathrm{i}} = \sum (c = 1 \ to \ 4) \ w_c \cdot p_{i,c} \tag{8}$$

where w_c is the weight of the criterion and $p_{i,c}$ is the AHP-normalized priority of site i under criterion c. This calculation yields the overall ranking.

3.2. Overall MCDA Scores and Ranking

The AHP includes a consistency check for pairwise comparison matrices via the consistency ratio. In the project process, the pairwise comparisons were adjusted to remain within acceptable consistency levels. In summary, the MCDA method steps are:

1. Construct the decision hierarchy (goal, criteria, alternatives);
2. Populate performance evidence for alternatives on each criterion using HY4RES site documents and datasets;
3. Normalize KPI indicators and retain the criterion-level AHP priority vectors used in the project scoring;

4. Determine criterion weights via AHP pairwise comparisons;
5. Calculate the overall site scores using the weighted sum of criterion priorities;
6. Rank alternatives by overall score and interpret trade-offs;
7. Evaluate robustness through sensitivity analysis.

To examine preference sensitivity, alternative weighting scenarios are evaluated conceptually to determine whether the rank order is stable. The base weights reflect a technology- and environment-oriented perspective consistent with HY4RES objectives.

Alternative scenarios include an environment-emphasized case, a social-emphasized case, an economic-emphasized case, and an equal weight case, in line with common MCDA robustness checks. For each scenario, overall scores are recomputed using the same within-criterion priorities to identify potential rank swaps and to interpret which criteria drive each alternative performance.

Within-site scenario variation is acknowledged in the project documentation, but for the cross-site comparison, each site is represented by the scenario or configuration used in the shared project dataset and results sheets to ensure comparability.

In summary, the methodology combines quantified KPIs derived from shared HY4RES economic and site analyses (Figure 5) with structured AHP-based aggregation and explicit sensitivity checks (Table 6), consistent with good practice in sustainable energy system evaluation.

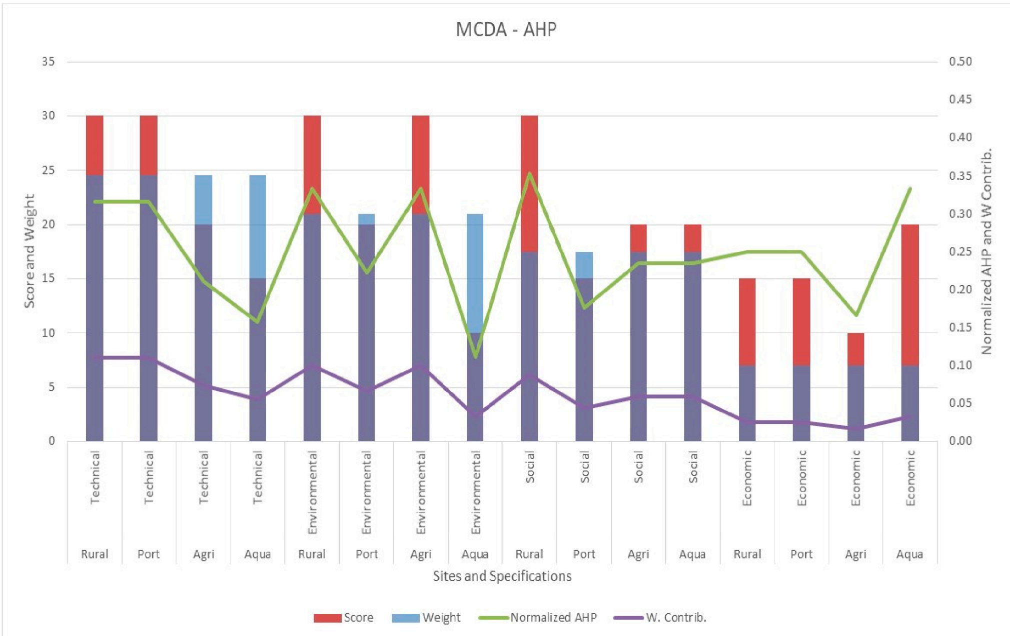


Figure 5. Four dimensions in each pilot (Tech, Env, Soc, Econ): multi-criteria decision analysis using Analytical Hierarchy Process.

The resulting ranking for the selected parameters is: first rural; second agriculture; third aquaculture; and fourth port. The analysis presented in Table 6 reveals that the rural site achieves the highest overall ranking (1.117), driven by its dominant performance in the technical and social categories. It is closely followed by the agriculture site (1.076), which serves as a strong runner-up due to its significant environmental impact and scale-dependent outcomes. In contrast, the aquaculture and port sites recorded lower aggregate scores, primarily due to trade-offs between economic autonomy and environmental or social breadth. The ranking of rural should be interpreted as identifying the strongest flagship demonstrator under the adopted criteria and weights, rather than the objectively best project under all possible value systems. In absolute terms, the agriculture pilot dominates in scale-dependent outcomes, particularly environmental value and aggregating emissions displacement, while the rural pilot leads because it concentrates technical integration learning and environmentally and socially mediated value in a single coherent narrative. Port presents excellent technical innovation and significant positive environmental evaluation. The ranking, therefore, reflects the prioritization of demonstrator quality and transferability of lessons, not the maximization of the magnitude of savings alone, as shown in Figure 6. The sector studies provide a consistent qualitative context for these outcomes, with the port emphasizing modeling and innovation in hybrid energy balance and the agriculture emphasizing operational integration and large-scale benefits.

Table 6. Weighted contributions and overall MCDA-AHP scores.

Site	Tech.	Env.	Social	Econ.	Normal	Ranking AHP	Key Strengths
Rural	0.110	0.100	0.088	0.025	3.4540	1.117	Best Overall: Dominates Technical & Social categories.
Port	0.110	0.067	0.044	0.025	2.3634	0.427	Technical: Very innovative but lower social breadth.
Agri	0.074	0.100	0.059	0.017	4.3167	1.076	Strong Runner-up: High environmental impact, moderate innovation.
Aqua	0.055	0.033	0.059	0.033	3.4509	0.624	Commercial: High economic autonomy but worst environment

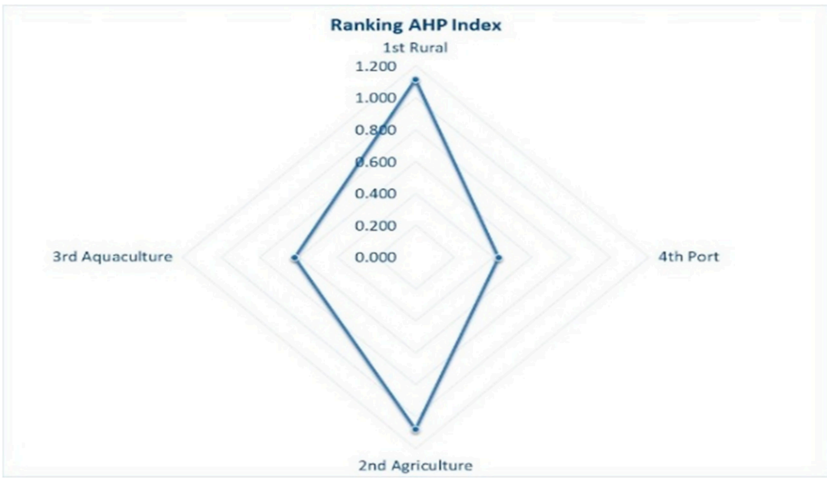


Figure 6. Ranking the AHP index.

This research presents a validation of the multi-criteria decision analysis (MCDA) performed to evaluate and rank four distinct pilot sites: rural, agriculture, aquaculture, and port. Utilizing the Analytic Hierarchy Process (AHP), the study prioritized four sustainability dimensions—technical, environmental, social, and economic—to identify the most viable flagship demonstrator.

Overall, the AHP framework successfully identifies the rural site as the most balanced and effective demonstrator under the current value system, providing a reliable foundation for future strategic investment and scaling.

The Analytic Hierarchy Process (AHP) was utilized to determine the priority weights for four sustainability criteria. To ensure the mathematical integrity of the decision-making process, a consistency check was performed on the pairwise comparison matrix. This check determines if the relative importance assigned to each criterion is logical and non-contradictory. The following parameters were derived from the weight distribution identified in the study (Table 7).

Table 7. AHP model.

Parameter	Value (Estimated)	Note
n	4	Number of criteria
RI	0.9	Constant for $n = 4$
λ max	4.001	Must be ≥ 4
CI	0.00033	Deviation from consistency
CR	0.036% < 0.10	Requirement for validity

For a model to be considered valid in AHP research, the consistency ratio (CR) must remain below the threshold of 10%. The specific consistency parameters for AHP analysis, namely λ max (Maximum Eigenvalue), CI (consistency index), and CR (consistency ratio), are typically part of the intermediate calculations (the pairwise comparison matrices). For a matrix to be considered "consistent" in the AHP, the consistency ratio (CR) must be less than 0.10 (or 10%). To ensure the mathematical integrity of the multi-criteria evaluation framework, a formal consistency check was performed on the 4×4 pairwise comparison matrix representing the core criteria dimensions (technical, environmental, social, and economic) ($n = 4$). According to Saaty's standard operational definition for a matrix of size $n = 4$, a Random Index (RI) of 0.90 is applied. Following the standard practice for a consistent matrix, the closer λ max is to n (which is 4), the more consistent the results. Generally, λ max usually falls between 4.00 and 4.25. Calculating the CI and CR for a λ max of 4.001 as follows: consistency index (CI) = λ max $-$ n/(n $-$ 1) = 0.00033 and for the consistency ratio (CR) = CI/RI = 0.00033/0.90 = 0.036%.

The calculated consistency ratio (CR) of 0.036% is significantly lower than the maximum allowable limit of 0.10. The near-zero CR indicates an exceptionally high level of logical transitiveness in the weight assignments. Hence, the exact pairwise comparison matrix represents how much more important one criterion is compared to another (Table 8). A value of 1 on the diagonal means a criterion is equal to itself, while values like 4.4 indicate that technical is moderately to strongly more important than economic.

Table 8. Pairwise comparison matrix.

Criteria	Technical	Environmental	Social	Economic	Priority Weight (wi)
Technical	1	1.1	1.25	4.4	0.341
Environmental	0.91	1	1.14	4	0.31
Social	0.8	0.88	1	3.52	0.272
Economic	0.23	0.25	0.28	1	0.077
Total	2.94	3.23	3.67	12.92	1

While the AHP model demonstrated exceptional consistency (CR = 0.036%), the following limitations should be noted, such as: (i) subjectivity of pairwise comparisons by the input values (e.g., technical being 1.1× more important than environmental) is based on expert judgment, as different stakeholder groups (e.g., local communities vs. private investors) might prioritize these differently; (ii) discrete scale constraints: since the Saaty 1–9 scale is discrete, small nuances in preference may be slightly "rounded" to fit the standard scale; and (iii) these rankings reflect the current pilot phase since, as projects scale, the economic weight might naturally increase, potentially favoring the aquaculture site in future iterations.

3.3. Discussion

3.3.1. Interpretation of Rankings

The MCDA outcomes provide a structured lens for interpreting how each HY4RES pilot aligns with a multi-dimensional set of objectives that combine technical demonstration, environmental performance, social relevance, and economic viability. Because the HY4RES pilots span very different sectors and scales, the ranking should be interpreted as a portfolio-oriented decision aid rather than a definitive statement of intrinsic superiority. Within that framing, the ranking pattern remains informative because it reveals which types of value are being prioritized under the adopted criteria and weights [14,16].

3.3.2. Rural Site as a Leading Option

The rural site emerging as the top-ranked option indicates that, under the adopted weighting scheme, balanced performance across technical, environmental, and social criteria outweighs the relatively weak economic performance associated with small-scale community systems [13]. This result is consistent with the HY4RES emphasis on demonstrating integrated hybrid solutions in real contexts, including rural settings where resilience, stakeholder engagement, and demonstrator visibility can be primary success conditions.

From a technical perspective, the rural configuration is explicitly framed as a multi-component hybrid microgrid integrating small hydropower, solar PV, wind, and BESS, with scenario-based sizing and optimization used to explore feasible designs. This multi-source integration directly supports the technical demonstration objective of HY4RES and aligns with the research emphasizing the design choices and optimization logic for small energy communities and hybrid renewable systems. In the criterion level AHP priorities, rural performs strongly on technical, and it also performs strongly on social, because the benefits are distributed across a community context rather than confined to a single commercial actor [5,14].

The social interpretation should also be expanded beyond direct electricity beneficiaries. The rural pilot generates value for the mill owners through restoration and renewed productive use, it strengthens rural tourism and place-based identity by creating a visible sustainability landmark, and it provides a practical reference case for private actors and small communities seeking energy independence. This indirect diffusion of value increases the relevance of the rural pilot as a demonstrator, because the main social mechanism is not only local consumption, but replication potential and narrative credibility across similar contexts. The social interpretation is reinforced by the rural documentation framing, which highlights the local context, stakeholder visibility, and cultural value of the watermill setting, supporting a narrative in which a renewable energy intervention is also a heritage and community development intervention [6]. Environmentally, the rural project is positioned as a primarily renewable supply for local loads, supporting low operational carbon intensity in the dataset. The economic weakness, reflected in comparatively modest NPV and higher LCOE for small systems, is therefore not interpreted as failure but as a known structural characteristic of community small-scale pilots, which can remain justifiable where public value and learning outcomes are primary.

The top ranking of the rural site is a direct consequence of the adopted strategic weighting system, which prioritizes non-commercial technical novelty, localized social benefits, and extreme carbon mitigation.

A critical implication is that the MCDA result effectively endorses a demonstration strategy in which pilot selection is not driven by immediate financial return, but by the combination of technical integration, learning, and public-facing social value. That interpretation is aligned with the publicly funded pilot rationale often adopted in regional innovation projects, where value creation includes replication pathways, social legitimacy, and evidence generation for future scaling.

3.3.3. Agriculture Versus Port as Impact-Based Scaling vs. Innovation-Based Integration

The near tie between the agriculture and port alternatives indicates that the decision boundary between them is sensitive to how one interprets the relative importance of immediate impact at scale versus technical novelty and sectoral strategic learning [9,10]. Both sites score strongly, but in different ways.

The agriculture case is supported by analyses of PV integrated with pumped storage with a pump as turbine operation in irrigation systems, where renewable supply fractions can be high and techno-economic performance can be strong due to the scale of electricity demand and the ability to schedule pumping within operational constraints. In the HY4RES dataset, this site carries very strong economic indicators and substantial environmental value in terms of reduced reliance on grid electricity for a large pumping load, which is consistent with the broader literature positioning irrigation electrification as a high-leverage decarbonization opportunity in water-intensive regions. Even though the agriculture configuration is comparatively standard in component types, its engineering challenge can be substantial because performance depends on operational coordination between water delivery requirements, storage behavior, and solar variability, which may not be fully captured by a simple component count in the technical criterion.

The port case, in contrast, is explicitly described as a micro-scale demonstrator integrating multiple resources and storage within a port environment, with associated work emphasizing modeling, optimization, and machine learning or data-driven management concepts to support operational performance [6]. Its primary contribution to a HY4RES-style portfolio is therefore learning and replicability in a maritime infrastructure context rather than immediate large-scale energy delivery. Because ports are strategic nodes for decarbonization and electrification, the port pilot may carry strategic option value that is not fully represented by per-site energy metrics, particularly if the demonstrator accelerates the adoption of hybrid modules or management systems in other ports [9].

The MCDA ordering placing irrigation slightly above the port under the adopted weights can be interpreted as a modest preference for environmental impact and broader beneficiary reach relative to novelty, given that environmental was weighted strongly and social remained less substantial. A technology commercialization-oriented perspective tests more novel integration in a harsh operational environment, while an emissions reduction-oriented perspective might elevate irrigation because it can deliver a larger magnitude of energy transition impact in the near term.

A critical point is that both agriculture and port have plausible replication narratives. Agriculture PV plus storage concepts can be replicated across irrigation districts, while modular port hybrids and advanced management concepts can be replicated across ports.

3.3.4. Aquaculture Site Ranking: Strong Business Case but Lower Portfolio Distinctiveness

The aquaculture site ranking presented in the MCDA does not imply weak project performance. Rather, it indicates that within the adopted criteria and weights, this pilot offers lower strategic distinctiveness relative to the rest of the portfolio, despite strong economic indicators. A critical reason is that the configuration builds substantially on existing assets, so the incremental contribution of the pilot lies primarily in optimization and joint component operational improvement rather than in demonstrating a new integration concept at the portfolio level. The primary beneficiaries also remain concentrated around the operating companies, which limits the breadth of social value compared with the rural pilot and reduces the suitability of the site as a flagship demonstration case. Interpreted in this way, the aquaculture pilot is best positioned as a strong private business case and a useful sector-specific validation study, rather than a reference project for the overall demonstrator pilots' narrative. In addition, the comparison between HY4RES modeling and other optimization approaches is itself a meaningful outcome for methodological validation and future decision support [11,12].

The lower ranking can be interpreted through three critical lenses. First, the aquaculture configuration builds substantially on existing assets and focuses on incremental optimization, which may be less aligned with a program objective centered on demonstrating new integration concepts. Second, the primary beneficiaries are the operating companies, so social value is comparatively concentrated rather than community-wide, even if employment and local economic stability remain important. Third, where the pathway includes biomass-related flexibility or combustion-adjacent components, even if renewable in accounting terms, this can complicate the narrative of zero emission electrification and can introduce operational and supply chain uncertainties, which can influence environmental interpretation within a portfolio that otherwise highlights electrified renewable integration. The result is that aquaculture remains a valuable pilot in a diversified set, but it is less compelling as a single flagship when the program seeks high-visibility public value and novel integration learning across sectors [6].

Overall, in this research, the ranking pattern suggests an implicit preference for pilots that either deliver broad community value or explore advanced integration in strategically important infrastructures, relative to pilots that primarily validate private economic performance in a single industrial facility.

3.4. Trade-Offs and Uncertainties

The ranking should be interpreted alongside trade-offs that may materially affect implementation success and perceived value. Because HY4RES pilots operate in real operational contexts, uncertainty is not limited to modeling parameters; it also includes governance, stakeholder acceptance, and integration constraints [6,13,16].

3.4.1. Economic Versus Non-Economic Value

The weighting scheme explicitly reduces the influence of pure financial return, which is coherent for public demonstration projects, but it also implies that economically strong projects such as irrigation and aquaculture may be underrepresented in the final ranking if stakeholders implicitly require financial self-sustainability or co-financing. Conversely, low or modest NPV projects can still be rational if they deliver learning value and social legitimacy, particularly in community pilots where long-term benefits may not be fully monetized in a standard cash flow framework.

A critical uncertainty is the sensitivity of small projects to cost overruns and resource variability. Rural community-scale pilots can cross from slightly positive to negative NPV with modest changes in capex, O and M, or resource yield assumptions, which can influence stakeholder narratives even when the project remains justified on public value grounds. Large-scale projects can also be sensitive, but the mechanisms differ: grid connection conditions, tariff structures for export, and operational constraints can dominate outcomes for large PV plus storage systems [10,12].

3.4.2. Environmental Performance Nuances

All pilots aim to improve environmental performance, but the nature of environmental value differs. The agriculture site delivers large-scale substitution of grid electricity for pumping, which can produce substantial absolute emission reductions, while the port and rural sites may deliver low-carbon-intensity electricity but at smaller absolute energy volumes. A key uncertainty is that the carbon intensity of grid electricity is not static over the project lifetime. If grid mixes decarbonize substantially, the operational carbon benefits of reducing grid imports may change relative to the present assumptions, affecting comparative environmental performance over time [2,3]. This does not remove the value of autonomy and resilience, but it can change climate accounting narratives, particularly for long-lived assets.

Site-specific environmental risks also exist. Port-based hydrokinetic devices require attention to local marine environmental interaction, even at a small scale, while river-based micro hydropower requires attention to ecological flow and local habitat conditions, particularly when adapting existing infrastructures. These considerations may not change the direction of benefit, but they affect implementation complexity and stakeholder perception.

3.4.3. Social and Governance Uncertainties

Social benefits can be high, but can also introduce project execution complexity. The inherent qualitative nature of social indicators and the associated limitations emphasize that sensitivity analysis and AHP consistency checks were used to maintain robustness and reduce arbitrariness in the final ranking. Community-anchored pilots may require more extensive stakeholder engagement, approvals, and coordination, potentially increasing schedule risk, even if social legitimacy is ultimately stronger. Cooperative-based projects, such as agriculture, can benefit many stakeholders but may involve internal governance processes that slow decision-making and create conservative preferences regarding operational risk. Port projects may have clearer governance boundaries, but high visibility can increase reputational risk if demonstrators underperform, while also increasing the upside of success as a replicable showcase.

3.4.4. Technical Uncertainties

Each pilot contains technical uncertainties that can affect performance outcomes relative to simulated KPIs. The rural and port demonstrators are the most novel in conception, component integration, and operational context, so the durability and performance of micro-scale devices and control strategies remain central uncertainties. The agriculture configuration is comparatively mature in components, but can face operational coordination uncertainties, including variability in solar yield and changes in water demand, which affect storage usage and grid import reliance. The aquaculture configuration faces uncertainty in how flexible demand concepts operate in practice under variable industrial schedules and whether surplus utilization pathways remain robust across production cycles. The rural configuration relies on the correct integration and maintenance of multiple micro-scale components, with seasonal hydrology and local solar and wind conditions influencing the realized autonomy level.

3.5. Sensitivity Analysis Results

Sensitivity analysis was used to test the robustness of the ranking to uncertainty in KPI inputs and to alternative weighting schemes. The sensitivity outcomes can be summarized as follows.

3.5.1. Sensitivity to Energy Price Uncertainty

Figure 7 shows how the net present value of the four pilots changes when electricity grid prices rise or fall, and the overall message is quite straightforward. Irrigation and port activities are highly sensitive to grid price variation: as grid prices increase, their NPV rises sharply, indicating that these sectors gain substantial economic advantage when electricity becomes more expensive, most likely because alternative energy sources or efficiency measures become comparatively more valuable [20,22–26]. Aquaculture and rural systems also benefit from higher grid prices, but their lines rise much more gently, meaning their financial performance is only mildly affected by electricity price swings. In essence, the graph highlights that the pilots with heavier electricity dependence experience the strongest economic gains when grid prices rise, while those with lower energy intensity remain relatively stable.

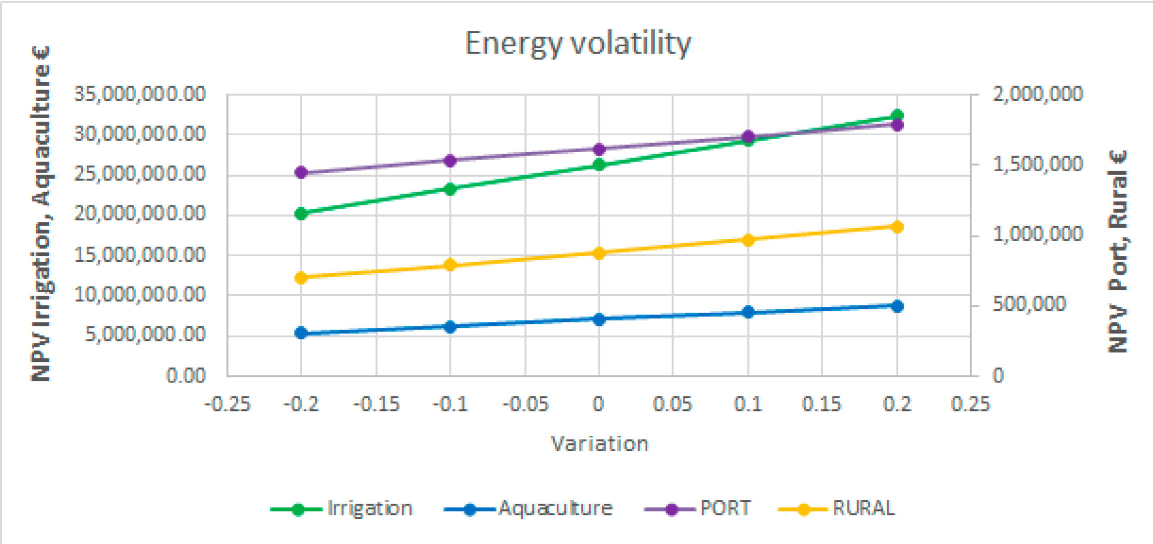


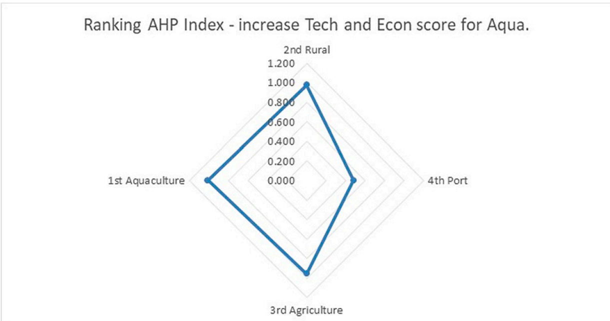
Figure 7. Sensitivity to the energy volatility.

3.5.2. Sensitivity to Criteria Weights

The weight variation scenarios reflect different stakeholder priorities, including increased emphasis on environmental, social, or economic criteria [20,22–26]. Because agriculture and port are close in the base case, modest changes in the relative importance of technical versus environmental criteria can lead to a swap between these two sites. The aquaculture site improves primarily under scenarios where the economic criterion weight is increased substantially relative to the technical and environmental criteria, since it has the highest economic priority, as presented in Figure 8a. This reinforces the interpretation that the preferred pilot depends on whether the decision prioritizes technical demonstration and environmental impact, as presented in Figure 8b, or prioritizes economic return, which is a central motivation for MCDA in hybrid renewable planning.

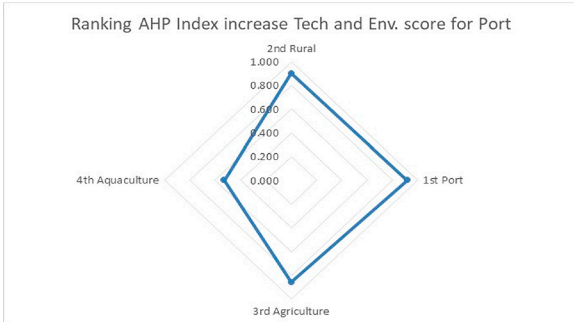
3.5.3. Machine Learning and Influence of Different Potential Factors

Across a full set of analyzed scenarios of the varying potential factors for the four competing dimensions (technical, environmental, social, and economic), Figure 9 illustrates how the relative importance of these dimensions shifts as the scenarios evolve and how this reflects different combinations of contextual conditions. In the rural pilot scenarios, the technological, environmental, and social dimensions often exert moderate to strong influence, suggesting that infrastructure readiness and ecological constraints are recurring considerations. The port pilot scenarios show a different profile, with technical and environmental factors frequently registering a strong influence. This pattern reflects the operational complexity and nature of port environments, where system performance is tightly coupled. The agricultural pilots display a more balanced distribution across all four dimensions. Environmental and social factors often rise prominently, highlighting the importance of ecological stewardship and community acceptance in agricultural contexts. Yet technological and economic influences also appear consistently, showing that innovation and financial sustainability remain essential considerations even in scenarios where environmental or social concerns dominate. The aqua pilot scenarios exhibit some of the widest variation, with technical and economic factors frequently reaching high-influence levels. This aligns with the inherent sensitivity of aquatic systems and the reliance on specialized technologies for monitoring, production, or resource management. Social and environmental influences appear more scattered, suggesting that their relevance depends heavily on the specific scenario conditions, such as market access, regulatory frameworks, or local community interactions. Taken together, Figure 9 portrays a landscape in which each scenario activates a different configuration of pressures and priorities. The four dimensions do not compete in a uniform way; instead, their influence is shaped by the unique characteristics of each pilot type and the contextual assumptions embedded in each scenario. This variability underscores the need for flexible strategies that can adapt to shifting combinations of technological demands, environmental constraints, social expectations, and economic realities.



Rank	Pilot Site	Overall Normal.	Ranking AHP Index	Key Strengths
2nd	Rural	3.4540	0.972	**Best Overall:** Dominates Technical & Social categories.
4th	Port	2.3634	0.482	**Technical:** Very innovative but lower social breadth.
3rd	Agriculture	4.3167	0.954	**Strong Runner-up:** High environmental impact, moderate innovation.
1st	Aquaculture	3.4509	1.013	**Commercial:** High economic autonomy but worst environment

(**a**)



Rank	Pilot Site	Overall Normal.	Ranking AHP Index	Key Strengths
2nd	Rural	3.4540	0.900	**Best Overall:** Dominates Technical & Social categories.
1st	Port	2.3634	0.915	**Technical:** Very innovative but lower social breadth.
3rd	Agriculture	4.3167	0.858	**Strong Runner-up:** High environmental impact, moderate innovation.
4th	Aquaculture	3.4509	0.529	**Commercial:** High economic autonomy but worst environment

(**b**)

Figure 8. Sensitivity to score variation factor: (**a**) aquaculture 1.013; (**b**) port 0.915.

To mathematically mitigate the limits of evaluating only four physical pilot sites, a robust, multi-dimensional dataset consisting of 42 distinct operational scenarios was programmatically generated. These scenarios represent structured combinations of conflicting criteria priorities (technical, environmental, social, economic) and operational volatility across the four sectors (rural, port, agriculture, aquaculture). The generation followed a grid search variation strategy within realistic boundary conditions: Weight Volatility Scenarios: Baseline AHP criteria weights were systematically varied by ±10%, ±20%, and ±30% to simulate diverse stakeholder preferences (e.g., a private investor heavily weighting economic returns vs. a public agency prioritizing carbon intensity or community benefit). Operational Volatility Scenarios: Site-specific KPI variables (such as grid energy price fluctuations, resource yield changes, and infrastructure readiness scores) were perturbed using a standard deviation step framework. All 42 scenarios mapped a total of 16 predictor variables (four sustainability criteria × four pilot alternatives) to evaluate the shifting AHP ranking index. Dataset partitioning was locked utilizing a fixed random state (rng(42,'twister') in MATLAB R2024b) and evaluated via a five-fold cross-validation scheme to guarantee complete algorithmic reproducibility.

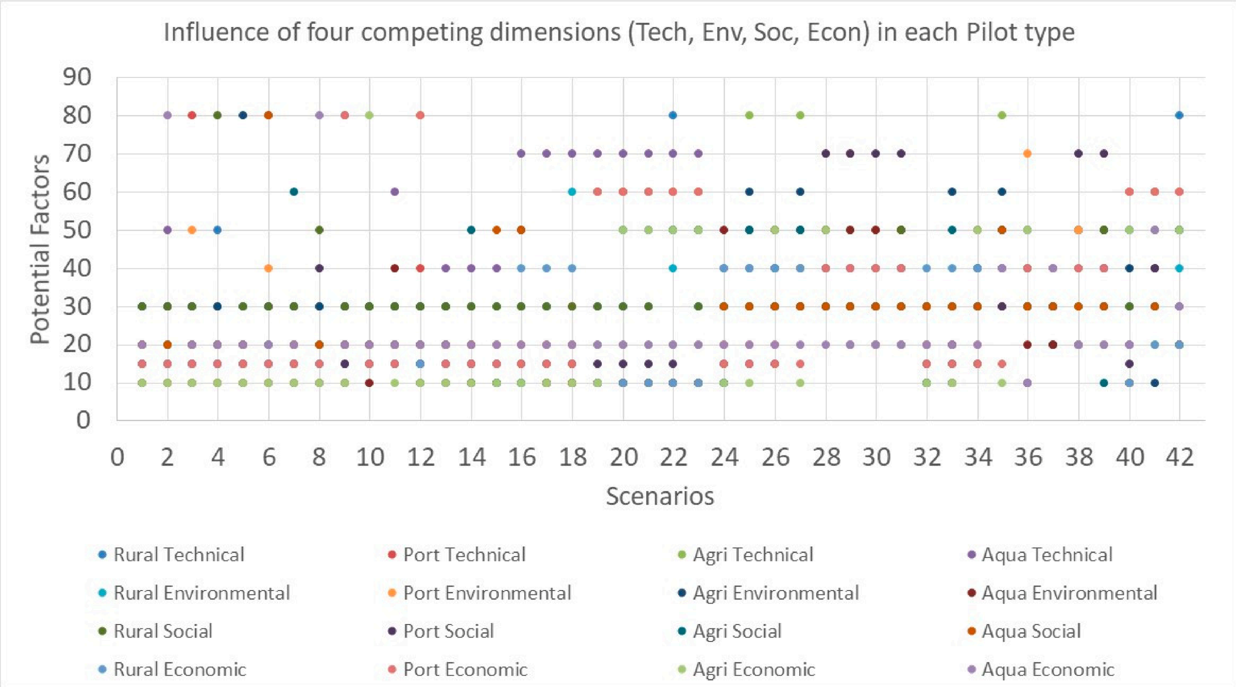


Figure 9. Scenarios and potential factors in the four competing in the technical, environmental, social, and economic dimensions.

Hence, the 42 scenarios were developed through a structured variation in the potential factors associated with the four decision dimensions—technical, environmental, social, and economic—across the four pilot sectors (rural, port, agriculture, aquaculture). Each scenario corresponds to a unique combination of contextual conditions, created by systematically varying the magnitude of key influencing parameters. These variations reflect plausible changes in

- Energy-related and operational conditions, such as fluctuations in energy prices, infrastructure readiness, or system performance constraints.
- Environmental pressures, including changes in ecological sensitivity, regulatory strictness, or resource availability.
- Social acceptance factors, such as community engagement levels or perceived societal benefits.
- Economic considerations, including investment requirements, market access, or cost–benefit expectations.

The ranges for these variations were defined based on the pilot-specific contextual analyses presented earlier in the manuscript. Each scenario was then encoded as a 16-dimensional input vector (four dimensions × four sectors), ensuring that the full spectrum of realistic operating conditions was represented. Figure 9 illustrates how these variations manifest across the scenario set, showing how different contextual assumptions shift the relative influence of the four dimensions.

To select the most suitable machine learning (ML) algorithm, three models were evaluated: Efficient Linear Support Vector Machine (EL-SVM), decision tree (DT), and efficient logistic regression (ELR). The performance of each model was assessed using precision, recall, and F1-score, as presented in Table 9. The EL-SVM algorithm achieved the best results, with precision values ranging from 0.94 to 1.00, recall between 0.88 and 1.00, and F1-scores from 0.93 to 1.00 across all classes. In contrast, the decision tree model showed the lowest performance, particularly for the aquaculture class. The ELR model produced the second-best performance, with results slightly lower than those obtained with EL-SVM.

Table 9. Computation of precision, recall and F1 for different ML algorithms.

Class	EL-SVM			DT			ELG		
	Precision	Recall	F1	Precision	Recall	F1	Precision	Recall	F1
Agriculture	0.94	1.00	0.97	0.94	0.83	0.88	0.94	0.88	0.91
Aquaculture	1.00	0.88	0.93	1.00	0.33	0.50	0.78	1.00	0.88
Port	1.00	1.00	1.00	0.83	0.83	0.83	1.00	0.83	0.91
Rural	1.00	1.00	1.00	0.61	0.92	0.73	0.92	0.92	0.92
Macro-F1			**0.975**			**0.735**			**0.905**

While the traditional AHP is robust for a single, fixed set of criteria weights, evaluating a wide landscape of varying contextual pressures (such as the 42 multi-dimensional operational scenarios explored here) is computationally intensive. The trained EL-SVM model acts as an efficient surrogate that accurately approximates the complex multi-criteria decision surface (macro-F1 = 0.975) instantly from a 16-dimensional input vector. A detailed application of the Efficient Linear Support Vector Machine (EL-SVM) model for predicting the optimal pilot site is developed. To inform the model training process and aid interpretability, the relationships between the predictor variables and the response variable across all 42 scenarios are illustrated in Figure 9. These 42 distinct operational profiles establish a baseline configuration and introduce controlled permutations to the normalized scoring matrices to simulate realistic systemic shocks: (i) Economic Scenarios (12 scenarios): Simulating grid tariff volatility ±15% to ±40% shifts in electricity purchase/sell pricing and CAPEX overruns, which directly shifted the net present value (NPV) and levelized cost of energy (LCOE) baselines. (ii) Environmental Scenarios (10 scenarios): Simulating the progressive decarbonization of the national grid energy mix (reducing the absolute carbon intensity of avoided grid imports by 20%, 40%, and 60%), as well as seasonal flow variations affecting hydro-ecological constraints. (iii) Technical Scenarios (10 scenarios): Varying the realized degree of hybridization, micro-grid component efficiencies, storage cycling degradation limits, and renewable resource availability (solar/wind yield drops or peaks by up to ±25%). (iv) Social/Governance Scenarios (10 scenarios): Testing variations in local community-anchored acceptance metrics, public visibility weights, and stakeholder cooperation readiness (adjusting qualitative scores within a [0, 1] interval).

The trained EL-SVM model was exported to Simulink for performing predictions, as shown in Figure 10. This figure includes an illustrative example of the model's operation using Scenario No. 4, 2, 5, and 3, respectively. Each scenario illustrates how a 16-dimensional input vector—comprising technical, environmental, social, and economic potential factors across four system sectors (rural, port, agriculture, aquaculture)—is processed to predict a dominant sectoral label. The four scenarios illustrate how different sectoral profiles lead the classifier to distinct predictions. For the selected analyzed scenarios, in case (a), the high rural values, particularly in the technical, environmental, and social potential factors, drive the model to classify the input as rural. In case (b), although most potential factors remain moderate, the aquaculture economic score reaches a high value, making it the dominant predicted sector. In case (c), the agriculture environmental potential factors stand out with a high value, leading the classifier to identify agriculture as the most representative label. Finally, in case (d), the port sector shows a strong technical value, supported by environmental and economic contributions, resulting in a port selection.

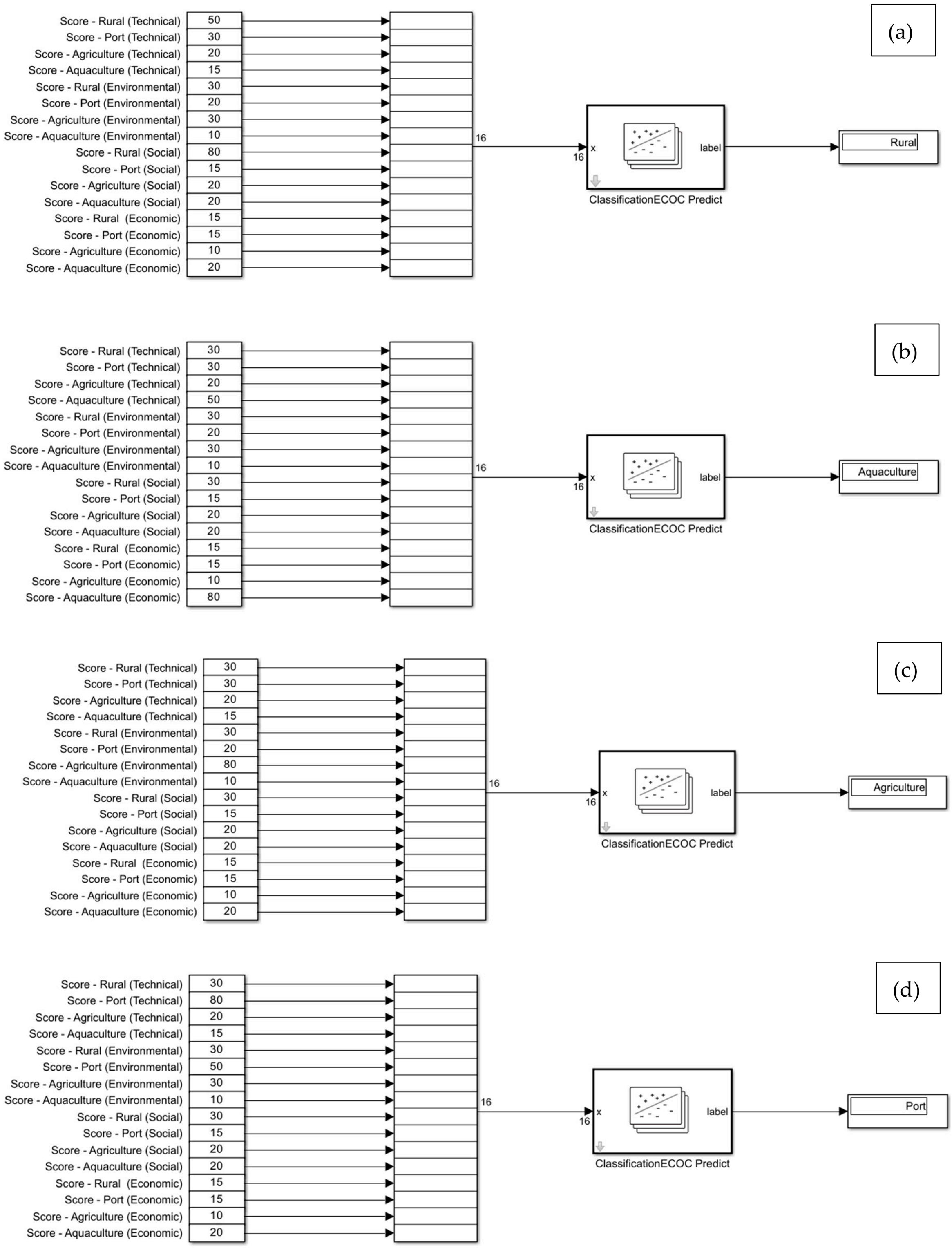


Figure 10. Sectoral classification outcomes using EL-SCM-based machine learning model, making predictions exported to Simulink: (**a**) Scenario 4; (**b**) Scenario 2; (**c**) Scenario 5; and (**d**) Scenario 3.

A principal advantage for decision-makers is that the algorithm, once exported to the Simulink environment, is robust and can serve as a practical tool for selecting the optimal pilot site. Table 10 presents the corresponding confusion matrix. The diagonal elements (highlighted in dark blue) indicate a correct prediction, representing a perfect fit for those instances. In contrast, any non-diagonal element (highlighted in light blue) signifies an incorrect classification. Considering the number of scenarios, an accuracy of 97.6% was achieved using the machine learning model.

Table 10. Confusion matrix for predicting the best pilot site.

		Predicted Class				
	Pilot Site	Agriculture	Aquaculture	Port	Rural	Total
True Class	Agriculture	16				16
	Aquaculture	1	7			8
	Port			6		6
	Rural				12	12
	Total	17	7	6	12	42

The confusion matrix summarizing the model's predictions for pilot site classification shows that the classifier performs very accurately across all four dimensions—agriculture, aquaculture, port, and rural—with only a single misclassification. Agriculture sites are predicted with perfect consistency: all 16 true agriculture instances are correctly identified, indicating strong model reliability for this class. Aquaculture also shows high accuracy, with seven out of eight sites correctly classified. Port and rural sites exhibit flawless classification, with all six port and all 12 rural instances correctly predicted.

Overall, the diagonal dominance of the matrix demonstrates that the model distinguishes the four pilot site types with exceptional precision. The absence of false positives or false negatives in three of the four classes suggests that the feature space provides clear separability for most dimensions. With 41 correct predictions, the classifier achieves near-perfect performance, reinforcing its suitability for supporting decisions on pilot site choice.

3.6. Methodological Limitations

Several limitations should be explicitly acknowledged, as they affect the degree of confidence with which the MCDA results can be interpreted. The AHP scoring process inherently involves expert judgment, since pairwise comparisons and the interpretation of criteria introduce an unavoidable element of subjectivity. Although the use of coursework-defined weights ensures methodological traceability, it also constrains the analysis to a predefined evaluative structure. The adopted weights (technical 35%, environmental 30%, social 25%, economic 10%) reflect the specific nature and objectives of the HY4RES research project.

The project centers on early-stage, publicly funded research pilots in which technological feasibility, environmental compliance, and social acceptance are the primary determinants of success. Within this context, economic profitability is not the dominant consideration, which justifies the lower weight assigned to the economic criterion. This weighting strategy aligns with the exploratory, pre-commercial character of the pilots, where the main goals are to understand system behavior, validate technological concepts, and assess societal and environmental impacts rather than to maximize financial returns. Consequently, the weight vector represents a deliberate value choice consistent with HY4RES priorities. Moreover, because the agriculture and port alternatives exhibit very similar scores, even small adjustments to the weights can alter their relative ranking, making the ordering of these two options particularly sensitive to preference changes. The analysis is also static, omitting explicit treatment of time, risk, and performance evolution, so differences between novel high-learning pilots and mature low-risk ones appear only indirectly. The KPI set is intentionally narrow and excludes dimensions such as replication potential, cultural or biodiversity impacts, and embodied emissions, which are only partially captured in broader categories. The KPI values also inherit uncertainties from modeling assumptions, and although sensitivity analysis helps, the results still depend on input quality. Even so, the MCDA remains useful for clarifying trade-offs and supporting transparent and structured decision discussions.

3.7. Stakeholder Engagement and Governance

The analysis reinforces that social value and governance readiness matter for successful deployment. The rural pilot benefits from strong community framing in the site documentation, but that framing implies a need for sustained local engagement and coordination with relevant authorities and stakeholders. The irrigation pilot requires cooperative-level alignment to ensure that energy optimization never compromises water delivery reliability, while the port pilot requires regulatory and operational coordination with port authorities for marine and infrastructure components. These governance considerations are not fully captured by numerical KPIs, so they should be treated as parallel decision criteria during implementation planning. The ranking supports tailored communication strategies. The rural pilot enables a community-centered narrative linking decarbonization with resilience and local value. The agriculture pilot enables an evidence-oriented narrative based on large-scale emissions and cost savings, well-suited for policy audiences focused on climate mitigation and agricultural sustainability. The port pilot enables an innovation narrative aligned with smart port and maritime infrastructure decarbonization agendas. The aquaculture pilot enables an industry narrative emphasizing the economic and operational feasibility of hybrid systems for aquaculture and fish processing facilities with biomass for drying kilns. Aligning each pilot to the stakeholder group it best addresses can maximize the overall project impact without requiring that every pilot serve the same public-facing role.

4. Conclusions

The objectives center on designing, evaluating, and selecting optimal hybrid renewable energy systems using a multi-criteria decision-making (MCDA) approach that integrates technical, economic, environmental, and social dimensions across different sectors. A separating finding can be identified into three clearly demarcated subsections: (i) Methodological Findings: Summarizing the success of embedding machine learning (such as EL-SVM) as a fast surrogate classifier to learn and reproduce complex AHP-based multi-criteria decision rules. (ii) Practical Implications: Highlighting how the framework assists project developers in balancing conflicting public socio-environmental values against private industrial efficiency across diverse sectors (rural, aquaculture, port, and agriculture). (iii) Limitations and Future Work: Outlining the expert-based dependency of the weighting system, the boundaries of the 42 generated scenarios, and how future studies can integrate broader real-time sensor data from external projects to increase generalizability. The assessment compared four HY4RES pilot sites using a KPI framework and an AHP-based MCDA approach aligned with the scoring and weighting defined in HY4RES datasets. The results highlight distinct strengths across sites and clarify why the preferred ordering emerges under the adopted criteria weights:

(i) The rural pilot at Moinho do Salto emerges as the most well-rounded option in the MCDA. It combines strong technical performance, through multi-source hybrid integration, with the highest social value in the dataset, while also achieving strong environmental performance. Its economic performance is comparatively weak in absolute terms due to the small scale, but the decision logic embedded in the weighting scheme places greater emphasis on demonstrator value, integration learning, and community relevance than on financial return, which explains why the rural site leads overall. In practical terms, this pilot best represents a community-centered hybrid demonstrator that can communicate the HY4RES objective of enabling clean energy transition in small and remote contexts through integrated solutions.

(ii) The agriculture pilot in Valle Inferior stands out for the magnitude of its benefits. Its configuration is associated with very strong economic indicators and substantial decarbonization potential within the shared HY4RES datasets, reflecting the leverage of integrating PV and storage with large pumping loads. Its rank shows the technical criterion priority is lower within the adopted AHP priorities, consistent with a framing that values novelty of integration over maturity of components, even when the operational challenge at scale is significant. This outcome implies that HY4RES can position the agriculture pilot as the primary quantitative impact case, delivering strong emissions and cost savings evidence, complementing the rural flagship narrative.

(iii) The port pilot is characterized by high technical novelty and strong alignment with innovation-oriented objectives in maritime infrastructure contexts. The port system is explicitly described as a demonstrator integrating multiple sources and storage in an operational port environment, with associated work emphasizing modeling, optimization, and advanced management concepts. Its ranking essentially ties with agriculture under small changes in preferences because high technical performance offsets weaker social breadth and modest direct economic benefit, which is expected for a micro-scale demonstrator. This supports the interpretation that the port pilot is strategically valuable as an innovation- and replication-oriented intervention, even when immediate energy output is not the dominant success metric.

(iv) The aquaculture pilot provides a strong business case and a credible sector-specific demonstration of hybrid operation in an industrial context, including modeling-oriented validation activities described in the HY4RES project. Its lower MCDA rank reflects the adopted scoring priorities, where its criterion-level technical and environmental shares are lower relative to the other pilots, and its social value is more concentrated in a limited beneficiary group.

The result should therefore be interpreted as a portfolio prioritization outcome rather than a judgment of feasibility. Within HY4RES, aquaculture still strengthens sector coverage and supports the claim that hybrid systems can be financially attractive for industrial facilities, but it is less suited as the single flagship when broader public value and novelty are strongly weighted. In the study's limitations, there is the context-specific nature of the HY4RES project and the inherent subjectivity of expert-based AHP weights. The small number of physical pilot sites was mathematically mitigated by developing 42 comprehensive operational scenarios. By systematically varying the criteria weights, input parameters, and environmental factors across all four pilots, a robust, multi-dimensional dataset was created that allowed the machine learning algorithms to learn generalized decision patterns beyond the static physical sites themselves.

Finally, the MCDA and ML approaches add decision transparency. ML allowed computational mapping, with rapid screening, being a surrogate approximation to the AHP. By explicitly combining criterion weights and criterion-level priorities, predictors and responses, the analyses clarify that selecting the rural pilot as the top choice follows from emphasizing technical demonstration, environmental performance, and social value over pure financial return. This transparency is valuable for stakeholder communication because it enables the project team to justify prioritization choices using a consistent framework tied to documented assumptions and dataset values. Overall, the results support a portfolio narrative in which the rural pilot is the flagship for community-centered hybrid integration, the agriculture pilot is the flagship for scale of impact, the port pilot is the flagship for innovation in maritime infrastructure, and the aquaculture pilot is a strong sector case for industrial feasibility and modeling validation.

In conclusion, the MCDA and ML results show that, under the HY4RES-aligned weighting potential factors, taken together, the four pilots illustrate that every option contributes essential value across different dimensions. When implemented as a coordinated portfolio and communicated strategically, they collectively demonstrate the versatility of hybrid renewable systems across community, agricultural, maritime, and industrial settings. This integrated approach strengthens HY4RES objectives by advancing decarbonization, fostering innovation, and deepening practical deployment knowledge throughout the Atlantic region.

The foundational data supporting the findings of this study are fully clear and accessible to ensure reproducibility. The complete dataset, including raw site-specific key performance indicators (KPIs), normalized scoring matrices, the tabular configurations for all 42 generated operational scenarios, and the surrogate machine learning outputs, can be accessed by request to the author.

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