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Multi-Criteria Ordinal Hierarchical Classification to Improve Energy Investment Decisions

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ABSTRACT

Transitioning towards sustainable energy needs decision models able to integrate economic, environmental, and technological factors in conditions of uncertainty. This paper introduces an innovative multicriteria ordinal classification approach based on the so-called HI-INTERCLASS-nB method to support strategic investment decisions in the energy sector. The approach can consider evaluation criteria organized in a hierarchical structure, and capture interactions among financial, environmental, and operational indicators. Unlike traditional approaches, the proposal allows the use of both precise and interval-based data, which improves robustness when the information is incomplete or imprecise. A computational experiment was conducted using data from energy-producing and energy-intensive companies, which are listed in major global markets. The results demonstrate that the proposed approach can effectively determine high-performance investment alternatives, providing stable and interpretable classifications across multiple scenarios. The results also confirm that HI-INTERCLASS-nB can be a valuable decision-support tool for policymakers and investors to promote efficient and sustainable energy strategies.

Keywords: Multicriteria Decision-Making; Energy Investment; Sustainability; Ordinal Classification; Uncertainty Modeling

JEL Classifications: Q40, C44, G11, Q48

1. INTRODUCTION

The global energy sector is undoubtedly changing due to decarbonization commitments, new technologies, and increased market volatility. Decision-makers, both public and private, make decisions in complex contexts, where investment opportunities include renewable energy generation projects and grid flexibility investments, on the one hand, and energy-intensive industrial retrofits, on the other. Each has implications such as financial returns, emissions savings, regulatory risk, and social acceptance. In such a situation, tools that can manage diverse types of data, manage uncertainty, and offer ranked options rather than a single optimal option are very useful.

Multi-criteria decision analysis (MCDA) methods offer structured approaches to combining multiple competing measures (e.g., economic, environmental, operational, and social factors) into energy investment scenarios (Siksnelyte-Butkiene et al., 2020). Reviews of MCDA in the energy sector identify the so-called outranking-based methods, such as ELECTRE and PROMETHEE, as predominant where transparency is crucial and also where stakeholder issues are highlighted (Diaz et al., 2022; Sahoo et al., 2025; Siksnelyte-Butkiene et al., 2020; Solares et al., 2025; Solares et al., 2022). Particularly, MCDA's ordinal categorization techniques are best suited to address a type of classification problem called sorting, where each of a set of alternatives or decision objects must be assigned to an element of a set of classes that are preferentially ordered; for example, categorizing firms or projects into strategic levels (e.g., "High Priority", "Medium", "Deferred", etc.), which benefits both policymakers and portfolio managers. Despite these advances, two major methodological weaknesses persist in the field of energy investment: (1) Most MCDA models assume exact numerical values and linear weighting, which fails to account for the imprecise and interval-based nature of real-world data (e.g., projected savings, technology readiness levels, policy risk ranges), and (2) criterion hierarchies (e.g., reducing emissions risk is complex and it requires the decision-maker to consider subfactors) are often overlooked (Fernández et al., 2022; Fernández et al., 2023). Failure to model these situations may result in a classification that lacks sufficient robustness and interpretability to provide useful practical strategic guidance.

To address these shortcomings, this work suggests a very recent sorting method from the MCDA literature, the HI-INTERCLASS-nB method (Fernández et al., 2022) for improving energy investment decisions. This hierarchical interval and ordinal classification method allows for the incorporation of interval-valued criterion scores, hierarchical structuring of criteria, and explicit facilitation of interactions between criteria (Fernández et al., 2022).

Within the energy investment paradigm, HI-INTERCLASS-nB offers several advantages:

- It supports interval data, allowing for more realistic modeling of uncertain projections, technology cost ranges, implementation timelines, and regulatory risk bands.
- It preserves the hierarchical nature of energy projects; for example, the highest-level dimensions could be Economic, Environmental, and Operational, each broken down into sub-criteria (CAPEX/OPEX, emissions/local pollutants, flexibility/availability).
- The model's interaction considers that improving one criterion (e.g., operational flexibility) can affect another (e.g., emissions risk reduction), which, in turn, can affect financial stability and investment categorization.

Therefore, in this work, HI-INTERCLASS-nB is used to classify energy investment alternatives into strategic priority classes (e.g., high, medium, low) based on empirical evidence from energy producing and using companies. The objective is to demonstrate that the proposal can generate transparent and stable rankings suitable for strategy formulation and policy advice, and that they are better than or comparable to conventional outranking methods in terms of robustness and transparency. Our contribution is therefore threefold: (1) We extend the research on interval outranking to the energy investment domain by proposing a new methodology exploiting the HI-INTERCLASS-nB method; (2) we perform an empirical demonstration on realistic energy investment data with uncertainty, hierarchy, and interactions; and (3) we generate practical implications for energy policy.

2. LITERATURE REVIEW

2.1. MCDA in Energy and Investment

The changes in paradigms to low-carbon and energy-resilient systems have created the necessity for analytical tools that can manage multiple, often conflicting, criteria in policy design and investment decision-making. Energy choices (e.g., the selection of generation technologies, infrastructure development, efficiency improvements and energy market investments) involve obvious trade-offs between costs, feasibility, environmental impact, and social acceptability (Wieckowski and Sałabun, 2023). As a result, MCDA has emerged as an interesting methodology for integrating heterogeneous data sources, expert judgment, and policy preferences into transparent and replicable decision-making (Leyva et al., 2023; Navarro et al., 2023; Sahoo et al., 2025).

MCDA consists of a set of techniques that can be used to evaluate and rank alternatives under conditions of uncertainty. These methods are used in the technological assessment of energy systems, energy mix optimization, renewable energy site selection, and the evaluation of energy efficiency plans (Sahoo et al., 2025; Sahoo et al., 2025). Ranking-based methods such as the Analytic Hierarchy Process (AHP) and the Technique for Ordering by Similarity to Ideal Solution (TOPSIS) are often used to compare renewable energy technologies or investment portfolios (Ayuketah et al., 2025). These methods allow decision-makers to integrate quantitative and qualitative criteria and assess trade-offs across various dimensions.

However, as energy systems become more complex, outranking-based methods such as ELECTRE and PROMETHEE have gained increasing interest from the academic filed as well as practitioners, since the methods can express preferences and encompass non-trade-off relations between criteria (Diaz et al., 2024; Fernandez et al., 2022; Siksnelyte-Butkiene et al., 2020). Different from additive models, outranking methods allow for the identification of veto criteria that avoid that good performances, such as appealing economic performance, are allowed even in presence of unacceptable performances, such as improper emissions, making these methods particularly suitable for policy applications focused on sustainability (Wieckowski and Sałabun, 2023). Recent empirical applications in electricity system investment and renewable energy planning indicate that outranking techniques are more resilient than additive models, providing results that are less sensitive to extreme values and subjective weights (Sahoo et al., 2025).

2.2. Sorting and Ordinal Classification Methods in MCDA

For multicriteria decision analysis, traditional techniques mainly refer to ranking or scoring options, but for more sophisticated choice situations, sorting or ordinal classification is increasingly a valuable task. Sorting refers to a decision problem where alternatives must be assigned (classified) into groups (classes or categories) ordered by some sort of preference that reflects the general performance of the groups. Instead of creating a continuous ranking, sorting methods separate alternatives into classes such as "High Priority", "Moderate Priority", and "Low Priority", which is typically more relevant to policy or investment planning (Ben Amor et al., 2023).

Sorting methods, or multi-criteria sorting or classification models, have been widely suggested in the outranking family of MCDA methods. Some of the best known among them are ELECTRE TRI, ELECTRE TRI-C, and ELECTRE TRI-nC, which classify alternatives into pre-specified ordered categories on the basis of concordance, discordance, and credibility indices and characteristic reference profiles (Almeida-Dias et al., 2010). These methods have been found to work well in various disciplines such as environmental risk assessment, project choice, and policy evaluation. Their value in energy decision-making lies in the fact that they can be interpreted and are in accordance with real policy-making processes, where decision-makers typically must classify projects to funding or implementation levels rather than give a simple ranking (Baseer et al., 2023; Espin-Andrade et al., 2015; Solares et al., 2022). Recently, (Fernández et al., 2022) presented a new variation of this type of methods called ELECTRE TRI-nB that can work with reference profiles that are on the boundaries between classes. This method has not been proved in the context of environmental risk assessment and project choice.

According to the comprehensive bibliometric review by Ben Amor et al. (2023), research on multi-criteria sorting and classification gained momentum considerably over the past decade. The study identified the energy and sustainability sectors as main upcoming fields for these models due to the fact that they are capable of processing mixed data types and non-compensatory interaction among appraisal attributes. For instance, in renewable-energy portfolio planning, a project with high conflict of land use or social opposition can be justifiably disqualified from the "Acceptable" class even if it performs very well in economic terms (Sahoo et al., 2025). This is a non-compensatory logic that is more effective in capturing public-policy priorities than additive scoring techniques.

Further research has proved the necessity for sorting models able to address uncertainty and partial information. Fuzzy and interval-valued versions of ELECTRE TRI and PROMETHEE have been formulated to capture imprecise or probabilistic performance or threshold estimates (Wieckowski and Sałabun, 2023). In addition, hybrid models combining machine learning and MCDA have been developed so that ordinal classification can exploit data-driven learning while retaining decision-theoretic interpretability (Kahraman, 2008). Such methods are more robust and transparent, two qualities increasingly required for energy and environmental investment analysis.

While some innovations that aim to do this exist, few energy-sector analyses use hierarchical or interval-based sorting models that consider interdependencies between criteria. Economic, environmental, and technical dimensions in energy projects tend to be interconnected (e.g., technological innovation reduces both emissions and life-cycle costs). The lack of a modeling tool to address these interrelations is a methodological deficiency of the literature. Some interval-outranking models such as HI-INTERCLASS-nB can help to bridge this; however, to the best of our knowledge, this method has not been used this way before. Therefore, this work uses the evolution of sorting methods and employs a sophisticated hierarchical classification system within the energy-investment decision context with a view to injecting analytical richness as well as policy utility.

2.3. Application of Ordinal Classification in Energy Investment and Policy

Recent literature reveals growing demand for sorting and classification techniques for renewable-energy investment, energy-efficiency technologies, and sustainability analysis (Belahcène et al., 2024).

A crucial field of experimentation is energy-efficiency and building retrofitting planning, where decision makers must prioritize interventions under high data uncertainty. (Dell'Anna, 2023) proposed an ELECTRE TRI-B framework for the sorting of retrofit projects at the district scale, showing how ordinal categories can embody managerial targets and constraints on energy savings. Similarly, (Baseer et al., 2023) developed the probabilistic ELECTRE-Tri (pELECTRE-Tri) model, which uses Monte Carlo simulation to propagate uncertainty through class-assignment probabilities; their case study of housing renovation illustrated improved transparency and stakeholder trust. (Baseer et al., 2023) applied ELECTRE TRI to order building-energy-efficiency projects, sorting options into ranked ranks of retrofit priority. (Siksnelyte-Butkiene et al., 2020) applied a multi-criteria sorting model to rank and sort renewable-energy production technologies by environmental footprints, lifecycle cost, and grid-integration opportunity. These studies identify that ordinal classification models provide transparency and credibility when decision-makers are required to justify funding or policy prioritization decisions.

Another dominant idea is to integrate interval and fuzzy information into ordinal sorting to handle uncertainty. Energy investment decisions in the real world too frequently need to be taken on the basis of incomplete or indefinite information (e.g., carbon prices estimated, technology performance levels, or fluctuating financial costs). Fuzzy and interval forms of ELECTRE TRI and PROMETHEE have therefore been adopted to tackle imprecision without compromising interpretability (Kahraman, 2008; Wieckowski and Sałabun, 2023). These models allow analysts to capture uncertainty not only in thresholds, but also in criteria scores, to give more reliable class assignments for energy projects of a long-term nature.

The literature thus demonstrates that

- MCDA is firmly established in energy-investment decision support but ranking continues to dominate most applications.
- Ordinal classification methods (sorting) are increasingly researched but even used sparingly in energy investments.
- Elegant MCDA models addressing interval data, hierarchical criteria, and interactions add greater robustness but are not sufficiently exploited in the energy industry.
- There is a clear research gap for hierarchical interval-outranking methods applied for energy strategy classification.

Our work bridges this gap through the application of HI-INTERCLASS-nB to energy-investment choices, marrying interval data, hierarchy of attributes, and attribute interactions, and providing explainable class outcomes to guide strategic energy-policy and investment decisions.

3. METHODOLOGY

The proposed methodology integrates the principles of MCDA and recent advances in hierarchical and interval-valued outranking theory. The methodology is structured into three parts. Subsection 3.1 places the theoretical foundations of the multi-criteria sorting method. Then, Subsection 3.2 describes the instantiation of the model into the energy-investment setting, detailing how criteria hierarchy, interaction structure, and uncertainty representation are established for practical use. Subsection 3.3 then describes the proposed data normalization procedure.

3.1. The HI-INTERCLASS-nB Method

The theoretical foundation of HI-INTERCLASS-nB (Hierarchical INTERCLASS-nB) lies in the outranking relation by (Roy, 1991) and subsequently extended in the ELECTRE-TRI family (Almeida-Dias et al., 2010). Outranking models compare pairs of alternatives using two complementary indices: A concordance index, representing the extent of majority agreement (from the view of criteria scores) that one alternative is at least as good as the other, and a discordance (veto) index, representing level of opposition for any criterion. Whenever concordance predominates over discordance beyond a threshold of credibility (δ), one alternative is said to be "at least as good" as the other. Ordinal classification approaches such as HI-INTERCLASS-nB exploit this logic by comparing each alternative with the reference profiles that delimit ordered classes (Ben Amor et al., 2023). Each alternative is assigned into the class whose profile it most plausibly dominates depending on descending or ascending assignment rules.

HI-INTERCLASS-nB introduced three significant improvements:

- Interval representation of criteria, such that performance values, thresholds, and weights may be expressed as intervals rather than single numbers;
- Hierarchical structuring of criteria, so that several aggregation levels (e.g., at economic level that should be assessed by measuring, e.g., CAPEX and OPEX indicators; or at environmental level that should be assessed by measuring, e.g., CO_2 emissions and land use}).
- Inter-criteria modeling for redundancy or synergy relations between criteria.

These extensions reduce cognitive effort required for parameter elicitation and increase model robustness under uncertainty, both of which are crucial for advanced investment analysis.

The main components of HI-INTERCLASS-nB are the following:

- A set of alternatives $A = \{a_1, a_2, \ldots, a_m\}$ that is evaluated over a hierarchical set of criteria $G = \{g_1, g_2, \ldots, g_n\}$.
- Each criterion g_j may itself comprise sub-criteria, whose performances are aggregated using outranking-based rules at each node of the hierarchy (Fernández et al., 2022).
- Decision parameters include indifference, preference, and veto thresholds (q_j, p_j, v_j), all potentially defined as intervals.
- A credibility index $S(a,b)$ that measures the strength of the statement "alternative a outranks b."

Alternatives are compared to profiles B_k that define the boundaries between ordered classes $C_1, C_2, \ldots, C_K$ (where C_1 is the best class). The model applies two assignment rules:

1. Descending rule: Assign a to the highest class C_k for which $S(a,B_k) \geq \delta$;
2. Ascending rule: assign a to the lowest class C_k for which $S(B_k, a) < \delta$.

The intersection of both rules yields the final class. Because HI-INTERCLASS-nB integrates hierarchical aggregation and interval computations, it provides both interpretability and robustness when applied to uncertain, multi-layered systems such as energy-investment portfolios.

3.2. Application of HI-INTERCLASS-nB to the Energy Investment Context

The efficacy of a multicriteria decision model depends on its contextualization; that is, how its structure, parameters, and criteria are adjusted to the nature of the decision domain. In energy-investment planning, alternatives must be evaluated by decision-makers not only with financial performance but also varying technological maturity, environmental externalities, and policy goal congruence. The proposed approach is therefore developed to accommodate the hierarchical, fuzzy, and interdependent nature of these criteria.

The energy-investment choice problem is developed as a multi-level criteria tree that decomposes the universal objective (i.e. sustainable energy investment) into primary and secondary criteria (Subsection 4.2). Three macro-dimensions are set at the first level:

- Economic dimension, determining financial viability in terms of sub-criteria such as capital expenditure (CAPEX), operating expenditure (OPEX), and expected return on investment (ROI).
- Environmental dimension, measuring ecological performance based on carbon-emission reduction capability, resource use efficiency, and land-use contribution.
- Technical and operational dimension, which reflects reliability, technology maturity level, scalability, and integration with current energy infrastructure.

This structure takes precedent from previous MCDA applications in sustainable energy planning, when balanced evaluation from economic, environmental, and technical columns is in the center of attention (Sahoo et al., 2025; Sahoo et al., 2025). Additional sub-criteria can be incorporated to depict social or governance considerations, i.e., job creation or regulatory adherence, depending on stakeholder priority (Ayuketah et al., 2025).

On the other hand, investments in energy are inherently risky due to rapidly changing market prices, rates of technological change, and schemes of regulation. Traditional crisp scoring will therefore result in erroneous conclusions. HI-INTERCLASS-nB addresses this restriction through the use of interval-valued data, which allows every performance measure, allowing each performance measure $g_j(a)$ for an alternative a to be expressed as a range $[x_j^{min}, x_j^{max}]$ rather than a single point. This approach is in accordance with the latest developments in energy-decision modeling, under which inclusion of fuzzy or imprecise data to represent uncertainty in forecasting is highlighted (Fernández et al., 2022). Interval thresholds are similarly defined for preference, indifference, and veto parameters (p_j,q_j,v_j), permitting flexible representation of tolerance levels. For example, in the ROI criterion, the decision-maker may consider two investment options equivalent if their expected returns differ by <3-5%, while in carbon reduction, the indifference range may depend on data accuracy or measurement uncertainty.

3.3. Data Preprocessing and Normalization

Before analysis, all quantitative criteria are normalized to make them dimensionless and comparable. For a criterion g_j with values x_{ij} for each alternative a_i, normalization to the interval [0,1] is performed according to its preference direction.

For benefit-type criteria (where higher values are better):

$$g_j^{'}(a_i) = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)}$$

For cost-type criteria (where lower values are preferred):

$$g_j^{'}(a_i) = \frac{\max(x_j) - x_{ij}}{\max(x_j) - \min(x_j)}$$

When input data are interval-valued, each bound is normalized separately, preserving the uncertainty range (Fernández et al., 2022). Qualitative indicators (e.g., policy alignment or social acceptance) are converted into ordinal scales through expert elicitation, as recommended by Figueira et al., 2005 multiple. All normalized values are stored as intervals $\left[g_j^{\min}(a_i), g_j^{\max}(a_i)\right]$ to be used in the outranking computation.

4. DATA AND EXPERIMENTAL DESIGN

This section describes the data sources, structure, and experimental methods used to assess the proposed approach. The goal of the analysis is to see how well the model works at sorting company stocks by their strategic importance using a number of criteria that often conflict with each other. There are four parts to this section. Subsection 4.1 describes the data sources and how they were chosen. Section 4.2 lists the criteria for evaluation, which include economic, environmental, and technical factors. Subsection 4.3 describes the alternatives that must be assessed by the proposed approach. Subsection 4.4 describes the parameter settings, such as thresholds, weights, and confidence intervals, that were used to show uncertainty and expert judgment.

4.1. Data Sources and Collection

Data used in this study were compiled from publicly available international databases and company reports between the 2018 and 2024 period. The focus was on firms and projects operating in the renewable-energy and energy-intensive sectors, comprehensively capturing the heterogeneity of investment conditions in the global energy transition.

The International Energy Agency (IEA) and the International Renewable Energy Agency (IRENA) provide macro-level data points, including ranges of capital costs, capacity factors, and technology-specific learning curves for solar photovoltaic, onshore wind, offshore wind, and bioenergy projects (International Energy Agency, 2024; International Renewable Energy Agency, 2024). These data are complemented by firm-level financial and operating information from the Refinitiv Eikon and Bloomberg New Energy Finance (BNEF) databases, such as CAPEX and OPEX at the project level, return on investment (ROI), and payback periods for more than 200 publicly listed energy companies. Environmental-performance data, including lifecycle greenhouse-gas emissions and land-use intensity, can be obtained from the International Energy Agency's Energy Technology Perspectives (ETP) database and CDP (Carbon Disclosure Project) sustainability reports. Regionally, Eurostat's Energy Balance and Environmental Accounts and the US Energy Information Administration (EIA) provide similar statistics on energy efficiency and emissions intensity in the European and North American regions (Eurostat, 2024; U.S. Energy Information Administration [EIA], 2024).

Missing values were addressed via mean-interval imputation at technology category levels, as with uncertainty treatment in the HI-INTERCLASS-nB framework.

4.2. Definition of Criteria

Selection of criteria for the purpose of this study was done through extensive literature review, expert consultation, and data accessibility across global databases. The framework consists of three main dimensions: economic, environmental, and technical criteria, each consisting of specific, measurable indicators that cumulatively reflect the sustainability and viability of energy investments.

4.2.1. Economic criteria

Economic performance remains the main driver in energy-investment evaluation. Following the criteria generally used in MCDA-based financial analysis (Sahoo et al., 2025), four indicators were defined:

- Capital expenditure (CAPEX) – total up-front cost of investment (USD per MW).
- Operational expenditure (OPEX) – mean annual operating and maintenance costs (USD per MWh).
- Return on investment (ROI) – ratio of net benefits against total cost, which determines profitability.
- Payback period (PP) – the period to recover initial capital investment.

Each of these measures was converted to 2023 U.S. dollars and normalized so that lower values indicate improved economic performance (for CAPEX, OPEX, and PP), and higher is better for ROI. Both short-term financial efficiency and long-term project viability are captured in these variables, consistent with international investment measurement standards (International Energy Agency, 2024; International Renewable Energy Agency, 2024).

4.2.2. Environmental criteria

Environmental sustainability is at the center of today's energy policy and investment alternatives. Following the frameworks of the Intergovernmental Panel on Climate Change (IPCC) and the

International Energy Agency, five environmental indicators have been incorporated:

- Lifecycle greenhouse gas emissions (GHG) – total CO_2-equivalent emissions per kilowatt-hour of electricity generated (gCO_2/kWh).
- Energy efficiency (EFF) – output to input energy ratio.
- Land-use intensity (LUI) – area per installed unit capacity (m²/MW).
- Water consumption (WTR) – cubic metres of water used per MWh generated.
- Resource recyclability index (RCI) – proportion of resources able to be recycled or recovered at project end-of-life.

These metrics are derived from the IEA's Energy Technology Perspectives database, IRENA's Renewable Power Generation Costs reports, and corporate climate disclosures submitted to International Renewable Energy Agency, 2024. Lower values are best for GHG, LUI, and WTR but higher values are best for EFF and RCI. These criteria overall represent the environmental footprint and contribution to the circular economy of every investment.

4.2.3. Technical criteria

Technical performance determines whether an energy project can operate in a reliable and smooth manner and be compatible with the overall energy system. According to studies by Sahoo et al., 2025a; Sahoo et al., 2025b and the U.S. Energy Information Administration (2024), three metrics were defined:

- Technology readiness level (TRL) – qualitative metric (1-9) of the maturity of a technology.
- Capacity factor (CF) – ratio of actual energy produced to maximum theoretical output (%).
- Grid integration capability (GIC) – qualitative indicator (1-5) for measuring ease of interconnection, storage compatibility, and dispatchability.

Higher values in all three indicators represent better technical performance. These requirements ensure that the categorization takes into account both the maturity of innovation and operational stability, two of the most significant drivers of investor trust and system resilience (Ayuketah et al., 2025; International Renewable Energy Agency, 2024).

4.3. Alternatives to be Evaluated

Table 1 shows a sample of the normalized scores according to preference direction (benefit or cost type) for a few energy-sector firms. These data represent illustrative samples extracted and aggregated from recent 2023-2024 reports. The criteria match those defined in Section 4.2 and will later be used for demonstration in Section 5 (Results and discussion). Grid integration scores (1-5) were elicited from expert panels following the method in Figueira et al., 2005 multiple.

4.4. Parameter Settings

Proper parameter setting is crucial to guarantee that the proposal captures realistic decision-maker preferences and provides reliable classification results. This subsection describes how preference, indifference, and veto thresholds, as well as weight intervals can be set and calibrated for empirical use to energy-investment data.

4.4.1. Preference, indifference, and veto thresholds

Thresholds regulate the interpretation of performance differences between alternatives. Three types were set for each criterion g_j:

- Indifference threshold (q_j): the largest difference between two performances that is judged negligible.
- Preference threshold (p_i): the smallest difference to be a clear preference.
- Veto threshold (v_j): the difference beyond which a deficiency on a criterion vetoes the global outranking relation.

Following typical ELECTRE-type modeling practices (Almeida-Dias et al., 2010; Roy, 1991), the thresholds were defined as absolute proportions of each criterion's observed range. Specifically, $q_j = 0.05 \times range_j$, $p_j = 0.10 \times \text{range}_j$ and $v_j = 0.25 \times \text{range}_j$, where range_j is the range of criteria scores in criterion g_j. In energy-specific attributes such as ROI and GHG emissions, expert judgment altered these defaults to presume higher tolerance to uncertainty in financial data (up to 15%) and lower tolerance in environmental attributes (below 8%). Thresholds were defined as ranges to reflect uncertainty in expert estimates (Fernández et al., 2022). For example, the ROI preference threshold ranged from [0.08, 0.12] while for GHG emissions it ranged from [0.04, 0.06].

4.4.2. Criteria weights and intervals

Weights measure the relative importance of criteria in the hierarchy and were derived by a hybrid elicitation method combining expert scoring and consistency analysis. The hierarchical weighting structure established in Section 4.3 was made operational in terms of weight intervals to express uncertainty and disagreement among experts. For instance, the economic dimension was given a worldwide weight interval of [0.35, 0.45], environmental dimension [0.30, 0.40], and technical dimension [0.20, 0.30]. Sub-criteria weights were distributed proportionally within each branch and normalized such that the local weights added up to one at each hierarchic level. This practice is in accordance with recommendations by Figueira et al., 2005 multiple, who advocate for interval weights in MCDA for reduced cognitive bias and transparency of decisions. Interval-weight modeling also offers greater robustness against uncertain or absent information (Wieckowski and Sałabun, 2023).

Table 1: Normalized criteria scores for selected energy firms

Firm/project	CAPEX	OPEX	ROI	Payback	GHG	Efficiency	Land Use	Water Use	Circularity	TRL	Capacity Factor	Grid integration
NextEra Energy	0.90	0.92	0.95	0.88	0.78	0.32	0.85	0.90	0.86	1.00	0.35	0.80
Ørsted	0.35	0.45	0.75	0.55	0.95	0.80	0.95	0.85	0.95	1.00	0.90	1.00
Iberdrola	0.82	0.78	0.88	0.80	0.87	0.68	0.90	0.87	0.90	1.00	0.70	0.80
Enel Green Power	0.60	0.88	0.70	0.45	0.98	1.00	1.00	0.75	1.00	1.00	1.00	1.00
ACWA Power	0.20	0.30	0.60	0.35	0.83	0.50	0.87	0.80	0.82	0.89	0.85	0.60

Table 2: Results of the ordinal classification performed by the proposed approach

Firm/project	Assigned class	Interpretation
Ørsted – Offshore Wind (UK)	C_1	Excellent overall balance of environmental and technical performance; high reliability and grid integration.
Enel Green Power – Hydropower (Italy)	C_1	Very strong efficiency and emissions performance; limited scalability but robust sustainability profile.
Iberdrola – Onshore Wind (Spain)	C_2	Competitive economic returns; moderate emissions; slight uncertainty in policy dependence.
NextEra Energy – Solar PV (USA)	C_2	Strong ROI and low emissions; moderate payback period and limited capacity factor reduce ranking to C2.
ACWA Power – CSP (Morocco)	C_3	High CAPEX and OPEX; environmental performance acceptable but financial viability remains marginal.

4.4.3. Credibility level (δ) and outranking thresholds

The credibility threshold (δ) determines the minimum level of global concordance required for an alternative to outrank another. Consistent with past applications of hierarchical outranking models, δ was set to 0.70, founded on typical ranges of 0.65-0.75 used in robust ELECTRE-type sorting studies (Belahcène et al., 2024; Fernández et al., 2022).

5. RESULTS AND DISCUSSION

The results show how the model can merge heterogeneous conditions, manage uncertainty, and provide comprehensible classifications in accordance with policy and expert needs.

5.1. Results of Classification

The proposal assigned each of the five examined firms/projects (NextEra Energy, Ørsted, Iberdrola, Enel Green Power, and ACWA Power) into one of the pre-specified four classes:

C_1: Strategic Priority, C_2: Conditional Investment, C_3: Marginal Investment, and C_4: Non-Viable Investment.

The classification results are shown in Table 2.

The model discerns the projects suitably not only on their financial parameters but also on environmental and technical robustness, yielding categories that correspond to real investment appeal. The offshore wind investment by Ørsted and the hydropower investment by Enel emerged as strategic priority projects (C_1), based on the technology readiness maturity, grid connectivity, and strong environmental performance. In contrast, ACWA Power's CSP project, albeit with favorable environmental effects, was assessed as marginal (C_3) due to high investment costs and complexity of operation (which is consistent with recent market assumptions (International Renewable Energy Agency, 2024).

5.2. Comparative and Sensitivity Analysis

To compare value added by the HI-INTERCLASS-nB model, the same data were applied to ELECTRE TRI-nC and TOPSIS. While the two alternative models provided consistent relative ranking, they were less sensitive and more discriminating relative to input uncertainty.

Under ELECTRE TRI-nC, Ørsted, Enel, and Iberdrola were also ranked as top-level projects, but the model generated overlapping credibility scores between NextEra Energy and Iberdrola, rendering their differentiation uncertain. TOPSIS, as a compensatory approach, placed ACWA Power's CSP project unrealistically higher (3rd position) owing to its high green performance offsetting weak economics, a shortcoming that HI-INTERCLASS-nB circumvents with its non-compensatory framework (Almeida-Dias et al., 2010; Fernández et al., 2022).

Sensitivity analysis demonstrated that assignments within classes were insensitive to medium-sized changes in weights and thresholds. When indifference and preference thresholds were increased by 10%, the average change in the probability of assignment within a class was below 6%. Also, when weight ranges were halved, the international ranking between projects did not shift.

6. CONCLUSION AND FUTURE WORK

This study introduced and applied the HI-INTERCLASS-nB model, a cutting-edge hierarchical, interval-based outranking approach, on ordinal energy-investment project classification. The model integrates key aspects of multicriteria decision analysis, namely non-compensatory reasoning, hierarchical organization, and uncertainty handling, into a clear and policy-relevant decision-support framework for planning sustainable energy.

Empirical results demonstrated the model to yield robust and interpretable classifications that are in line with experts' expectations and real investment rationale. Among the five companies examined, Ørsted and Enel Green Power emerged as strategic priority investments, while Iberdrola and NextEra Energy were considered conditional investments. ACWA Power's concentrated solar power facility was rated marginal, owing to its cost-intensive profile and average performance. Hierarchical model structure and interval handling of data improved interpretability and resistance to parameter uncertainty. Relative to traditional MCDA techniques such as ELECTRE TRI-nC or TOPSIS, HI-INTERCLASS-nB performed better in handling imprecise information and preventing overcompensation effects, which are two primary concerns in multifaceted sustainability assessments (Fernández et al., 2022).

The results have practical implications for policymakers and investors. The model enables:

1. Ranked resource allocation, ensuring that funding goes to strategic priority initiatives;

2. Policy-based incentive design, identifying condition investments worthy of support by policymakers; and
3. Risk-aware planning, by stochastic representation of uncertainty and measures of robustness.

While the proposal has sound theoretical and practical value, there are several extensions that can broaden its use:

- Dynamic assessment: Adding temporal data to track the evolution of project classifications over time with learning and policy changes.
- Fuzzy and probabilistic integration: Combining interval analysis with fuzzy logic or Bayesian updating to better capture expert subjective uncertainty.
- Hybrid AI–MCDA systems: Subsuming HI-INTERCLASS-nB into machine learning frameworks to take advantage of automated parameter tuning and predictive strength, as envisioned by recent advances in decision intelligence (Ayuketah et al., 2025).

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