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Supporting Sustainable Energy Finance through Hierarchical Multi-criteria Sorting of Electricity Generation Technologies

Efrain Solares[1], Raymundo Diaz[2]*, Juan Manuel Sanchez[3], Eduardo Fernández[1], Juan Antonio Granados Montelongo[4], Juan Antonio Álvarez Gaona[5]

[1]Faculty of Accounting and Administration, Autonomous University of Coahuila, Torreón, Mexico, [2]Business School, Tecnologico de Monterrey, Monterrey, Mexico, [3]Department of Accounting, The University of Texas at San Antonio, San Antonio, United States, [4]Department of Renewable Natural Resources, Antonio Narro Autonomous Agrarian University, Saltillo, Mexico, [5]Faculty of Marketing, Autonomous University of Coahuila, Saltillo, Mexico. *Email: raymundo.diaz@tec.mx

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ABSTRACT

Sustainable finance requires decision-support tools capable of integrating financial indicators with environmental and social risk factors in a transparent and data-driven manner. This study introduces a hierarchical multi-criteria sorting approach for the evaluation of electricity generation technologies, aimed at informing capital allocation and investment screening decisions. The framework relies exclusively on quantitative criteria obtained from public datasets and organizes them into a structured hierarchy encompassing economic performance, technical reliability, system relevance, and environmental and health impacts. Interval-valued evaluations and preference parameters are employed to represent uncertainty and heterogeneity in financial decision contexts. The resulting range-based classifications distinguish technologies according to their overall acceptability from a sustainable finance perspective. Results for the U.S. electricity sector highlight the ability of the approach to support responsible investment decisions under multiple, potentially conflicting financial and sustainability considerations.

Keywords: Electricity Generation Technologies, Multi-criteria Decision Analysis, Sustainability Assessment, Ordinal Classification (Sorting)
JEL Classifications: Q40, C44, G11, Q48

1. INTRODUCTION

Electricity generation technologies are the pillar of modern energy systems and play a fundamental role in economic development, environmental sustainability, and social well-being. Decisions regarding the implementation and expansion of generation technologies have long-term implications for energy costs, greenhouse gas emissions, land use, public health, and energy security. As energy systems suffer a rapid transition driven by climate goals, technological innovation, and regulatory changes, the need for a systematic and transparent assessment of electricity generation options becomes critical.

The evaluation of electricity generation technologies is inherently a multidimensional problem. Technologies differ in their investment and operating costs, as well as in their emissions profiles, local environmental impacts, land-use requirements, and health and safety implications. These dimensions often involve conflicting objectives: technologies with low capital costs may have high emissions or health impacts, while technologies with favorable environmental performance may face higher upfront costs or spatial limitations. Therefore, relying only on single indicators, such as the levelized cost of electricity (LCOE) or carbon intensity, can provide a misleading basis for decision-making. Thus, multi-criteria decision analysis (MCDA) has been widely employed to support energy planning and technology assessment. MCDA frameworks enable decision-makers to integrate heterogeneous criteria into a structured evaluation process, improving transparency and facilitating the comparison of diverse technological options.

Despite the widespread use of MCDA in energy planning and technology assessment, the current literature presents several methodological limitations. First, many studies rely on fully compensatory aggregation (e.g., additive value models or weighted sums) or hybrid ranking procedures, where good performance in one dimension can offset poor or unacceptable performance in others. This is often problematic in energy policy contexts, where non-negotiable requirements exist (e.g., extremely bad emissions or public health effects), and can reduce the interpretability of the results for decision-makers (Sahabuddin and Khan, 2021).

Second, much of the literature is concentrated on assessing technology to produce a ranking rather than an evaluation to produce the sorting of the alternatives (i.e., assigning the technologies to preferentially ordered classes). In practice, policymakers often need to assign technologies to ordered categories such as "highly sustainable," "acceptable," or "unacceptable," which is more aligned with selection, eligibility standards, and strategic planning in decision aiding than with establishing a strict ranking. While multi-criteria classification models have been consolidated and analyzed within the decision-support community, their systematic use in energy technology assessment remains rather limited (Belahcène et al., 2024).

Third, existing studies often employ flat lists of criteria, even when the decision context naturally suggests a hierarchical structure (e.g., environmental impact broken down into climate, local pollutants, land use, and water impacts). Flat structures limit the ability to audit decisions and understand the contribution of each dimension at different levels of aggregation. Hierarchical ranking methods exist, such as the Multi-Criteria Hierarchy Process (MCHP) combined with ELECTRE TRI, but they are not yet routinely adopted in energy assessment workflows (Corrente et al., 2016). Fourth, uncertainty is often addressed through informal sensitivity analyses, maintaining both precise assessments and preference parameters. However, to a certain extent, energy technology indicators often vary due to data heterogeneity (e.g., life-cycle assessment ranges), contextual variability, and incomplete articulation of stakeholder preferences. Interval modeling provides a robust way to represent imperfect knowledge and incomplete preference information in ordinal ranking based on the outranking approach (Fernández et al., 2019; Fernandez et al., 2020). However, the integration of (i) hierarchical criteria structures, (ii) interval-based criteria scores and preference representation, together with (iii) the evaluation of electricity generation technologies has remained unexplored.

Therefore, this work addresses these limitations by proposing a multi-criteria hierarchical classification framework to assess electricity generation technologies, designed to be transparent, auditable, and robust to imperfect information. The proposed approach offers three methodological advances. First, the evaluation criteria are structured hierarchically, reflecting the decomposition used in energy planning and enabling consistent aggregation across levels (Corrente et al., 2016); the proposal structures the assessment using a hierarchy of criteria encompassing techno-economic performance, local environmental impacts, climate-related emissions, land-use intensity, and health and safety effects. Second, the framework allows evaluation at any level of the hierarchy, generating not only an overall class assignment but also intermediate-level assignments that provide diagnostic information on whether a technology is primarily disadvantaged by economic performance, local pollutants, climate impacts, or land-use constraints. Third, both (a) the scores for the alternative criteria and (b) the parameters representing decision-makers' preferences are modeled using intervals, allowing the model to reflect data variability and preference imprecision in a unified manner (Fernández et al., 2019; Fernandez et al., 2020; Fernández et al., 2022a). A case study is used to show the applicability of the proposal. All criteria used in this case study are based on quantitative indicators obtained directly from public databases, ensuring transparency, consistency, and reproducibility.

The remainder of the paper is organized as follows: Section 2 describes the related work; Section 3 details the criteria hierarchy, datasets, and the proposed hierarchical interval sorting model; Section 4 presents the empirical study for six major electricity generation technologies in the United States; and Section 5 discusses policy implications, limitations, and future research directions.

2. LITERATURE REVIEW

The evaluation of electricity generation technologies has been widely addressed in the literature due to the economic, environmental, and social implications associated with technology choice (Filemon et al., 2025; Hemmati et al., 2024; Undurraga et al., 2024). Conventional and renewable generation options differ substantially in terms of investment and operating costs, emissions, land use, and impacts on human health. As a result, this problem has been commonly formulated as a multi-dimensional decision task that requires the simultaneous consideration of heterogeneous and often conflicting criteria (Barros et al., 2020; Mardani et al., 2021).

Several review studies highlight the widespread adoption of MCDA in the energy sector and emphasize its ability to accommodate economic, environmental, technical, and social indicators within a single analytical framework (Mardani et al., 2021). For example, (Hernández-Torres et al., 2025) proposed an integrated MCDA framework using a hybrid combination of AHP and a distance-based method to assess the sustainability of power generation technologies, illustrating how trade-offs among cost, emissions, and reliability criteria can be managed in technology selection. Similarly, (Şengül et al., 2015) applied fuzzy TOPSIS to rank renewable and conventional generation options under economic and environmental criteria, highlighting the importance of simultaneously considering multiple performance indicators in energy planning decisions. Amiri et al. (2024) used AHP–TOPSIS in a case of grid capacity expansion, but acknowledged that compensatory aggregation may mask serious trade-offs between economic and environmental criteria.

These are examples of ranking-oriented methods. In practice, however, energy planning and policy decisions often require broader classifications, such as determining whether a technology is acceptable or unacceptable, or assigning technologies to priority groups for deployment. Therefore, this type of methods can be unrealistic in real-world energy decision contexts when energy planners and policymakers aim to classify technologies into ordered categories, such as "highly sustainable", "acceptable", or "unsuitable", to support regulatory thresholds, eligibility rules, or strategic roadmaps. Multiple-criteria sorting models provide a natural framework for assigning alternatives to ordered classes based on their multi-dimensional performance (Figueira et al., 2005).

Within the family of MCDA methods, outranking-based sorting methods, such as ELECTRE TRI, are particularly attractive because they support non-compensatory reasoning and allow for the explicit treatment of discordance. Recent surveys have consolidated the theoretical foundations of this type of sorting methods and clarified their relevance for policy-oriented decision problems (Bouyssou et al., 2024). Dell'Anna (2023) demonstrated the use of ELECTRE TRI-C to classify energy efficiency projects into priority tiers, illustrating the practical value of sorting when stakeholders require assignment to discrete categories rather than rankings. Bouyssou et al. (2024) provided a comprehensive overview of multiple-criteria sorting approaches, underscoring their theoretical foundations and suitability for problems where thresholds and veto effects are critical.

Despite the evident attractiveness of these methods, a lack of clarity in the data aggregation process has been acknowledged (Sahabuddin and Khan, 2021). In practice, the weighting process can be carried out by several experts, but inconsistencies may exist. Recent advances in sustainability assessment recognize the greater sensitivity of the weighting process, which has been acknowledged as an important step in the MCDA, enabling the integration of different stakeholders (Wulf et al., 2023).

Interval modeling is a method for addressing imperfect knowledge. Fernández et al. (2019) introduced an interval-based classification approach for multi-criteria ordinal classification (sorting) problems, illustrating the incorporation of interval-valued information into classification rules (Fernández et al., 2019). Building on this (Fernández et al., 2020) introduced further interval-based extensions for ordinal classification problems for ELECTRE TRI-type outranking methods to address candidate assignments in terms of imperfect knowledge.

In parallel, several authors have emphasized the importance of hierarchical criteria structures in complex decision problems. Energy technology assessment often involves natural decompositions (e.g., environmental impact can be subdivided into climate change, local air pollutants, land use, and water consumption). Corrente et al. (2016) address this gap by introducing the Multiple Criteria Hierarchy Process (MCHP) for ELECTRE TRI methods, enabling sorting decisions with hierarchically structured criteria and consistent weight propagation across levels. While this contribution provides a rigorous methodological foundation, its application in energy technology evaluation remains scarce, particularly in studies aiming at policy-relevant classification. Recently, hierarchical interval outranking classification models have been proposed to represent both the hierarchy and more complex preference models, such as interactions between criteria. The work of (Fernández et al., 2022a) presents a hierarchical, interval-based ranking model with interactive criteria, capable of representing synergy and redundancy effects, as well as ranking for assessments with interval values. These models appear particularly important for energy technology assessment, since many key indicators (life cycle emissions, land-use intensity, health risks, etc.) are intrinsically based on intervals.

One disadvantage of MCDA in applied energy is the reproducibility problem, as the data have been collected using undisclosed research methods or scoring systems due to uncertain sources. On the other hand, an experimental design with data-driven analysis may help improve reproducibility. For the US, the National Renewable Energy Laboratory's Annual Technology Baseline provides a comprehensive resource that documents the current cost and performance characteristics of generation options in a manner suitable for comparative analysis (Mirletz et al., 2024). Regarding comparative data on other impacts, related metrics are provided in aggregate by generation type. An interesting set of databases, Our World in Data, offers downloadable comparative data on deaths per Terawatt-hour (TWh) and land-use intensity per MWh in a harmonized format, summarizing findings from peer-reviewed literature in relevant published reports (Our World in Data, 2022; 2025).

However, despite the fact that these datasets are open to the public, a methodological gap persists in the research: most empirical studies fail to integrate three aspects: (i) Hierarchical classification, (ii) multilevel evaluation results, and (iii) interval modeling of both performance and preferences within a general framework. This article addresses this research gap and proposes a methodology as a transparent and auditable decision support system for the hierarchical classification of electricity generation technology into classes ordered according to their sustainability characteristics.

3. METHODOLOGY

This section presents the methodological framework used to evaluate electricity generation technologies. It describes the formulation of the decision problem, the hierarchical structure of criteria, the modeling of alternatives' performances, and the decision rules applied to assign technologies to ordered classes.

The proposed approach relies on a hierarchical multi-criteria sorting model and explicitly accounts for imperfect information by allowing both criteria evaluations and preference parameters to be represented as intervals. The methodology is designed to ensure transparency, consistency across levels of the criteria hierarchy, and robustness of the final results and recommendations.

3.1. Problem Formalization

Let $A = \{a_1, a_2, \ldots, a_n\}$ be the finite set of alternatives, where each alternative a_i represents an electricity generation technology (e.g., coal, wind, solar).

The evaluation is conducted with respect to a finite set of criteria structured as a hierarchy. Let $\mathcal{G}$ denote the set of all criteria nodes in the hierarchy (see Subsection 3.2 for more details) and let $\mathcal{G}_E \subset \mathcal{G}$ be the subset of elementary criteria (i.e., leaves of the hierarchy). Each non-elementary criterion aggregates the information provided by its direct descendants (children).

For each alternative $a \in A$ and each elementary criterion $g \in \mathcal{G}_E$, the performance of a on g is denoted by $g(a)$, which represents a quantitative indicator (e.g., cost, emissions, land use). Due to uncertainty in the recollection of the data or imprecisions in the real world, many times the exact value of $g(a)$ is unknown. To account for data variability and imperfect information, these performances are modeled as intervals:

$$g(a) = [\underline{g}(a), \overline{g}(a)]$$

where $\underline{g}(a)$ and $\overline{g}(a)$ denote, respectively, the lower and upper bounds of the plausible performance of alternative a on criterion g.

The decision problem is then formulated as an ordinal classification (sorting) problem, where $C = \{C_1, C_2, \ldots, C_p\}$ is a finite and totally ordered set of classes, such that

$C_1 \prec C_2 \prec \cdots \prec C_p$, and higher-indexed classes correspond to higher levels of overall sustainability performance (i.e., C_i is more desirable than C_j; $i > j$).

The goal is to determine the most convenient assignments (from the perspective of a decision maker) of each alternative $a \in A$ to at least one class $C_h \in \mathcal{C}$. Such assignments are based on a hierarchical outranking-based sorting model. For this purpose, preference information from the decision maker is specified at each node (criterion) of the hierarchy. For example (see Subsections 3.4 and 3.5 for more details), let w_g denote the relative importance (weight) of criterion g, and let additional preference parameters (e.g., thresholds or cutting levels) be defined as required by the sorting procedure (Subsection 3.5). In line with the treatment of imperfect information, these parameters may also be represented as intervals:

$$w_g \in [\underline{w}_g, \overline{w}_g]$$

At each non-elementary criterion, the model aggregates the outranking relations of its descendants, ensuring consistency with the hierarchical structure. This aggregation allows the evaluation and classification of alternatives not only at the global level, but also at any intermediate level of the hierarchy.

The final class assignment for each alternative is obtained by comparing its overall performance with respect to predefined class profiles or decision rules, according to the selected hierarchical sorting procedure. The non-compensatory nature of the model ensures that insufficient performance on critical criteria can prevent assignment to higher classes, even if other criteria exhibit favorable values.

3.2. Criteria Hierarchy and Construction of Indicators

As introduced in the previous subsection, the evaluation of electricity generation technologies is conducted using a hierarchically structured family of criteria, denoted by,

$$\mathcal{G} = \{g_0\} \bigcup \mathcal{G}_I \bigcup \mathcal{G}_E,$$

Where g_0 represents the overall evaluation objective, $\mathcal{G}_I$ is the set of intermediate (non-elementary) criteria, and $\mathcal{G}_E$ is the set of elementary criteria. The hierarchy is defined as a tree, where each non-elementary criterion aggregates the information provided by its direct descendants exploiting the preferences of a decision maker.

The objective at the root of the hierarchy, g_0, is to assess the overall sustainability performance of electricity generation technologies; specifically, assign each technology to an ordinal class (e.g., {Very low, Low, Medium, High, Very high} sustainability/convenience). This objective is decomposed into four intermediate criteria reflecting dimensions that are standard in energy planning and technology assessment following recommendations of the literature (Lovering et al., 2022; Mardani et al., 2021; Markandya and Wilkinson, 2007; Our World in Data, 2022; 2025; Sovacool et al., 2016; Wachs and Engel, 2021; Wulf et al., 2023):

$$g_0 \rightarrow \{g_0, g_0, g_0, g_0\}$$

where:

- g_1 represents economic performance,
- g_2 represents technical performance,
- g_3 represents system relevance, and
- g_4 represents environmental and health impacts.

This decomposition is consistent with the standard sustainability assessment of energy technologies, which emphasizes economic feasibility, technical operability, system-level deployment, and environmental and social externalities as distinct but complementary dimensions (Lovering et al., 2022; Mardani et al., 2021; Markandya and Wilkinson, 2007; Wulf et al., 2025).

3.2.1. Economic performance

The economic performance criterion g_1 captures the cost characteristics of electricity generation technologies and is decomposed as:

$$g_1 \rightarrow \{g_{11}, g_{12}, g_{13}, g_{14}\}$$

where:

- g_{11} is the capital cost (USD/kW) – investment required to build a new electricity generation facility, normalized by installed capacity,
- g_{12} is the fixed operation and maintenance (O&M) cost (USD/kW·year) – recurring expenditures that are independent of electricity output, such as staffing, routine maintenance, insurance, and administrative expenses,
- g_{13} is the variable O&M cost (USD/MWh) – expenses that depend on electricity production, excluding fuel costs, such as consumables, waste handling, and variable maintenance, and
- g_{14} is the levelized cost of electricity (USD/MWh) – average cost of producing one unit of electricity over the lifetime of a generation asset, accounting for capital costs, operating costs, fuel costs, and financing assumptions.

These indicators are widely used in comparative assessments of generation technologies and provide a coherent representation of investment and operating costs under consistent modeling assumptions (Mirletz et al., 2024). They can be directly obtained from the Annual Technology Baseline published by the National Renewable Energy Laboratory and from the cost and performance studies of the U.S. Energy Information Administration.

3.2.2. Technical performance

The technical performance criterion g_2 reflects the operational characteristics of generation technologies and is defined as:

$$g_2 \rightarrow \{g_{21}\},$$

where g_{21} denotes the capacity factor. This indicator measures the utilization rate of installed capacity and can be directly extracted from the same source. Capacity factor is a fundamental indicator of technical performance and is commonly used to characterize the operational reliability and intermittency of electricity generation technologies (U.S. Energy Information Administration (EIA), 2024).

3.2.3. System relevance

The system relevance criterion g_3 captures the actual role of each technology in the electricity system and is decomposed as:

$$g_3 \rightarrow \{g_{31}, g_{32}\},$$

where:

- g_{31} is the existing installed capacity (MW) – total nominal generating capacity of all operational units of a given technology in the electricity system, and
- g_{32} is the net electricity generation (TWh) – total amount of electricity produced by a technology over a given period, after accounting for plant-level consumption.

These criteria can be extracted from the U.S. Energy Information Administration's *Electric Power Annual,* specifically regarding existing capacity and net generation. Unlike modeled cost indicators, these measures reflect observed deployment and operation, providing a system-level perspective on the relative importance of each technology in the current electricity mix (U.S. Energy Information Administration (EIA), 2024).

3.2.4. Environmental and health impacts

The environmental and health impacts criterion, g_4, represents non-market externalities associated with electricity generation and is decomposed as:

$$g_4 \rightarrow \{g_{41}, g_{42}, g_{43}\},$$

where:

- g_{41} is the life-cycle land-use intensity (m^2·year/MWh),
- g_{42} is the death rate from accidents and air pollution (deaths/TWh), and
- g_{43} is the life-cycle greenhouse gas emission intensity (gCO_2-eq/kWh).

All three criteria can be obtained directly from datasets published by Our World in Data, which synthesize peer-reviewed life-cycle assessment, epidemic, and emissions studies. Land-use intensity values can be derived from life-cycle assessments reported by UNECE and related studies, and are provided with minimum, median, and maximum estimates, making them suitable for interval-valued modeling (Lovering et al., 2022). Death rates aggregate accident-related and air-pollution-related mortality per unit of electricity generated, following established fuel-cycle health impact analyses (Markandya and Wilkinson, 2007; Sovacool et al., 2016). Life-cycle greenhouse gas emissions are reported as CO_2-equivalent intensities and reflect full life-cycle impacts rather than operational emissions alone (IPCC, 2022).

3.3. Performance Evaluation of Alternatives

Let

$$A = \{a_1, a_2, \ldots, a_m\} = \{coal,\ natural\ gas,\ nuclear,\ hyderpower,\ wind,\ and\ solar\ photovoltaic\}$$

denote the set of considered alternatives corresponding each to an electricity generation technology. The performance of each alternative is evaluated on the set of elementary criteria $\mathcal{G}_E$ defined in Subsection 3.2 and shown in Table 1. As stated before, for each elementary criterion $g \in \mathcal{G}_E$ and each alternative $a \in A$, the performance evaluation is denoted by $g(a)$. Depending on the nature of the available data, evaluations take the form of either point values or intervals. The collection of all evaluations defines the performance matrix:

$$G = \left(g(a)\right)_{a \in A,\, g \in \mathcal{G}_E}$$

For the economic criteria $g_{11}, g_{12}, g_{13}, g_{14}$ and the technical criterion g_{21}, each evaluation $g(a)$ is represented by a single numerical value. For Table 1, these values correspond to technology-level reference assumptions under a fixed scenario and reference year (moderate cost case and 2030). Capital cost values (e.g., $g_{11}(Coal)$ = 3905.6 USD/kw) represent the overnight investment cost of a new plant, normalized by installed capacity. For each technology, the reference configuration defined by the data provider is used (e.g., new coal plant with average capacity factor, combined-cycle natural gas plant, large-scale nuclear reactor). No aggregation across criteria is performed at this stage, and no normalization or scaling is applied. Fixed costs are expressed per unit of installed capacity and capture expenditures

Table 1: Description of the criteria considered to evaluate the technologies

Criterion	Meaning	Preference	Data type
g_{11}	Capital cost	Minimize	Real
g_{12}	Fixed O&M	Minimize	Real
g_{13}	Variable O&M	Minimize	Real
g_{14}	LCOE	Minimize	Real
g_{21}	Capacity factor	Maximize	Real
g_{31}	Installed capacity	Maximize	Real
g_{32}	Net generation	Maximize	Real
g_{41}	Deaths/TWh	Minimize	Interval
g_{42}	Land-use intensity	Minimize	Real
g_{43}	Life-cycle GHG	Minimize	Real

independent of output, while variable costs are expressed per unit of electricity generated and reflect production-dependent expenses. These values are taken directly from the same reference configurations used for capital costs.

When a criterion value is not reported for a given technology under consistent assumptions, the corresponding entry in the performance matrix is left undefined. Such cases are explicitly retained and handled at the decision-model level rather than through imputation.

System relevance criteria, g_{31} and g_{32}, capture the observed contribution of each technology to the electricity system. These values are obtained from the U.S. Energy Information Administration's Electric Power Annual, specifically regarding existing capacity and net generation. Unlike modeled cost indicators, these evaluations reflect historical deployment and operation, providing a complementary system-level perspective. Both criteria are expressed as absolute quantities and reflect actual deployment and operation. They are treated as benefit-type criteria, as higher values indicate greater system presence.

Environmental and health-related criteria are evaluated using normalized indicators expressed per unit of electricity generated according to the datasets provided by Our World in Data (Ritchie, 2020; 2022). For criteria g_{42} (death rate) and g_{43} (life-cycle greenhouse gas emissions), evaluations are represented as point values:

$$g_{42}\left(a\right) \in \mathbb{R}^{+}, \quad g_{43}(a) \in \mathbb{R}^{+}.$$

For the land-use intensity criterion g_{41}, evaluations are represented as intervals:

$$g_{41}(a) = \left[\underline{g}_{41}(a), \bar{g}_{41}(a)\right],$$

where the bounds correspond to the minimum and maximum values reported across life-cycle assessments. Interval-valued representation is used to preserve documented variability and to avoid selecting arbitrary representative values.

Each elementary criterion is associated with a well-defined preference direction. Cost-related, environmental, and health criteria are formulated as criteria to be minimized, whereas system relevance criteria are formulated as criteria to be maximized.

The performance matrix G provides the complete quantitative description of alternatives required to apply the hierarchical multi-criteria sorting model and is shown in Table 2.

3.4. Hierarchical Multi-criteria Sorting Procedure

As reported in Section 2, the ELECTRE family is the most prominent method using the so-called outranking approach, one of the leading approaches in the literature about decision-making. While traditional ELECTRE methods are effective in many scenarios, they have limitations when handling uncertain or imprecise data, which are common in real-world decision-making. Furthermore, many decision problems are highly complex, and to evaluate an alternative against a given criterion, it is necessary to also evaluate it against sub-criteria.

This is where the so-called interval-based hierarchical outranking approach comes into play (Fernández et al., 2022b). Below, we provide a brief explanation of this method. For the sake of consistency, we will use here the notation presented in (Fernández et al., 2022b).

- Let A be the set of alternatives (potential actions).
- Let Ig be the set of indices of all criteria in the hierarchy.
- Let $\chi = \{g_{0,} g_{1,...}, g_{card(Ig)}\}$ be the set of all criteria in the hierarchy. Without loss of generality, we assume that preference increases as a function of the values of the criteria.
- Let EL be the set of indices of all elementary criteria.
- Let N_h the number of immediate subcriteria of a non-elementary criterion g_h.
- Let $G_h = \{g_{h1},_{...}, g_{hNh}\}$ be the set of immediate subcriteria of a non-elementary criterion g_h.
- Let I_{Gh} the set of indices of all criteria in G_h.
- Let *EL(h) be* the set of indices of all elementary criteria that influence a non-elementary criterion g_h.
- Let *D(h) be* the set of indices of all criteria that influence a non-elementary criterion g_h of a lower hierarchical level; when $j \in D(h)$, then g_j It is said to be a descendant of g_h.
- Let $EL_{p,}$ a subset of EL, be the set of indices of all criteria that are pseudo-criteria, that is, the subset of criteria where the performance of the alternatives is not measured using interval numbers.
- Let $EL_{I,}$ a subset of EL, be the set of indices of all criteria that are interval numbers.

(Fernández et al., 2022b) recommend using a partial overcoming relationship, denoted as $Sj \subseteq A \times A$, associated with each criterion $g_j \in EL$. This serves to indicate that "*a* is at least as good as *b* from the perspective of g_j"; $a, b \in (A \times A)$, together with a degree of credibility, $\delta_j(a, b)$.

The calculation of δ_j (a, b) depends on whether g_j is a pseudo-criterion or an interval number. When g_j is an interval number, a possibility function is required to determine if a criteria score is

Table 2: Performance matrix

Technology	g_{11}	g_{12}	g_{13}	g_{14}	g_{15}	g_{31}	g_{32}	g_{41}	g_{42}	g_{43}
1. Coal	3905.6	83.3	8.99	—	—	197	828	[12, 21]	24.6	970
2. Natural Gas	1403.3	31.8	2.04	—	—	509	1 671	[0.9, 1.3]	2.8	440
3. Nuclear	7616.4	175.0	2.80	84.4	0.93	96	772	[0.2, 0.5]	1.3	24
4. Hydropower	8937.4	101.3	0.00	107.5	0.52	80	250	[14, 33]	0.04	11
5. Wind	1483.7	29.9	0.00	32.7	0.43	146	434	[0.4, 8.4]	0.03	6
6. Solar PV	1193.5	18.0	0.00	36.9	0.27	110	205	[12.6, 19]	0.02	53

at least as good as another. It is possible to define the possibility function as follows:

$$P(E \geq D) = \begin{cases} 1 & if \quad p_{ED} > 1, \\ p_{ED} & if \quad 0 \leq p_{ED} \leq 1, \\ 0 & if \quad p_{ED} < 0 \end{cases}$$

Where $E = [e^-, e^+]$ and $D = [d^-, d^+]$ are interval numbers and

$$p_{ED} = \frac{e^+ - d^-}{\left(e^+ - e^-\right) + \left(d^+ - d^-\right)}$$

When $e^+ = e^- = e$ and $d^+ = d^- = d$, $P(E \geq D) = \begin{cases} 1 & if\ e \geq d, \\ 0 & otherwise \end{cases}$

Therefore, when $g_j \in EL_I$, $\delta_j(a, b)$ can be calculated as follows:

$\delta_j(a, b) = P(g_j(a) \geq g_j(b))$;

And when $g_j \in EL_P$:

$$\delta_j(a,b) = \begin{cases} 1 & if \quad g_j(b) - g_j(a) \geq p_j, \\ \dfrac{g_j(a) - g_j(b) + p_j}{p_j - q_j} & if \quad g_j(b) - p_j \leq g_j(a) < g_j(b) - q_j \\ 0 & if \quad g_j(a) - g_j(b) \geq -q_j. \end{cases}$$

where p_j and q_j represent the preference and indifference thresholds for the criterion g_j. The former establishes a range in which the policymaker has a strict preference for one of the alternatives; the latter establishes a range in which the policymaker is indifferent given that the performance of the alternatives is sufficiently similar.

Now, the degree of credibility of aS_hb when $h \notin EL$, denoted by $\sigma_h(a,b)$, can be calculated recursively by summing all the σ_j(a, b) values to $g_j \in G_h$. Note that, when $g_j \in EL_N$, then:

$$\sigma_j(a, b) = \delta_j(a, b). \tag{1}$$

This aggregation requires a criterion weight (considered as a relative importance coefficient) that must be defined for each $g_j \in G_h$; let's denote this weight as w_{jh}. Other parameters associated with $g_j \in G_h$ can also be defined as a veto threshold, v_{jh} (rejecting any credibility of aS_hb if $g_j(b)$ exceeds $g_j(a)$ by an amount greater than v_{jh}). These parameters allow calculating a concordance index γ related to S_h, $c_h(a,b,\gamma)$. This value represents the support of the coalition of criteria according to aS_hb, where γ is the highest credibility value of these criteria that support the claim. The degree of credibility of the claim "the coalition of agreement γ considered is sufficiently strong" is then calculated as $P(c_h(a,b,\gamma) \geq \lambda_h)$, where λ_h is a threshold established by the policymaker to determine whether a solid majority is constituted. The reader is advised to consult (Fernández et al., 2022b) for more details on the calculation of $c_h(a,b,\gamma)$, as well as some restrictions that the aforementioned parameters must meet.

Using this notation, we can perform the ordinal classification of electricity generation technologies by using the following procedure (Fernández et al., 2022b). The HI-INTERCLASS-nC method is a novel approach that uses an interval-based hierarchical outranking model to assign alternatives to preferentially ordered classes. This methodology allows assignments to be made at the level of any non-elementary criterion g_h. C^h is defined as a finite set of classes $C^h = \{C_1, \ldots, C_k, \ldots, C_M\}^h$, $M \geq 2$, ordered with increasing preference with respect to g_h. The subset $R_k = \{r_{k,j}, j = 1, \ldots, \text{card}(R_k)\}$ represents the reference alternatives that characterize C_k, with $k = 1, \ldots, M$. The total set of reference alternatives is $\{r_0, R_1, \ldots, R_M, r_{M+1}\}$, where r_0 and r_{M+1} are the anti-ideal and ideal alternatives, respectively.

The credibility indices between an alternative a and class C_k are defined as:

$${}_h(\{a\}, R_k) = \max_{j=1,\ldots,card(R_k)} \left\{ {}_h(a, r_{k,j}) \right\}$$

$${}_h(R_k, \{a\}) = \max_{j=1,\ldots,card(R_k)} \left\{ {}_h(r_{k,j}, a) \right\}$$

Where ${}_h(a,r_{k,j})$ is calculated through equation (1).

For a given value $\beta > 0.5$, the hierarchical categorical classification relationships are defined as follows:

a) $aS_h(\beta)R_k \Leftrightarrow \sigma_h(\{a\}, R_k) \geq \beta$;

b) $R_kS_h(\beta)a$ Symbol $\sigma_h(R_k, \{a\}) \geq \beta$.

The selection function is defined as: $i_h(\{a\}, R_k) = \min\{\sigma_h(\{a\}, R_k), \sigma_h(R_k, \{a\})\}$.

The method uses two joint rules to suggest assignments: the descending rule and the ascending rule, which must be used together. Each of these rules selects only one class for the possible assignment of an alternative.

Descending assignment rule: First, establish β and λ. Then, define the class set C^h and the representative subsets of the alternatives $\{r_0, R_1, \ldots, R_M, r_{M+1}\}$.

- Compare a with R_k for $k = M, \ldots, 0$, up to the first value, k, such that $aS_h(\beta)R_k$.
- For $k = M$, select C_M as a possible category to assign a.
- For $0 < k < M$, if $i_h(\{a\}, R_k) \geq i_h(\{a\}, R_{k+1})$, then select C_k as a possible category to assign a; otherwise select C_{k+1}.
- For $k = 0$, select C_1 as a possible category to assign a.

Ascending assignment rule: First, establish β and λ. Then, define the class set C^h and the representative subsets of the alternatives $\{r_0, R_1, \ldots, R_M, r_{M+1}\}$.

- Compare a with R_k for $k = 1, \ldots, M+1$, up to the first value, k, such that $R_kS_h(\beta)a$.
- For $k = 1$, select C_1 as a possible category to assign a.
- For $1 < k < M+1$, if $i_h(\{a\}, R_k) \geq i_h(\{a\}, R_{k-1})$, then select C_k as a possible category to assign a; otherwise select C_{k-1}.
- For $k = M + 1$, select C_M as a possible category to assign a.

3.5. Preference Modeling

The assignment of alternatives to ordered classes requires the specification of preference information reflecting the decision maker's priorities and tolerance to imperfect knowledge. In this work, preference modeling is performed in a manner consistent with the hierarchical structure of criteria and with the use of interval-valued evaluations according to the aggregation rules described in subsection 3.4.

3.5.1. Criteria weights

The relative importance of criteria is modeled using weights. For each non-elementary criterion $g \in \mathcal{G}_I$, a vector of local weights is defined over its direct descendants. Let *ch*(*g*) denote the set of children of criterion *g*.

To account for imprecision in preference elicitation, weights are allowed to take the form of intervals:

$$w_h \in [\underline{w}_h, \overline{w}_h]$$

where the bounds represent admissible ranges reflecting uncertainty or variability in the decision maker's judgments. Interval-valued weights are specified independently at each node of the hierarchy and must satisfy:

$$0 \le \underline{w}_h \le \overline{w}_h, \forall h \in ch(g)$$

$$\sum_{h \in ch(g)} \underline{w}_h \le 1$$

$\sum_{h \in ch(g)} \overline{w}_h \ge 1$ Several elicitation strategies can be used to elicit the values of these parameters, depending on the availability, consistency, and cognitive effort expected from the decision maker (Singh and Pant, 2021; Solares et al., 2022; Solares et al., 2025). The first group of methods is based on direct assignment; the decision maker assigns weights directly to each criterion (Kizielewicz et al., 2024). A second group includes ratio-based methods, where the decision maker compares criteria in terms of relative importance (e.g., Figueira and Roy, 2002). This can be done by stating how many times one criterion is more important than another, or by allocating a fixed number of points among criteria. Another possibility is indirect or learning-based approaches. In these methods, weights are inferred from example decisions, preference statements, or observed choices. The elicited weights, often expressed as feasible intervals, are those that best reproduce the decision maker's observed behavior while respecting the hierarchical constraints (e.g., Fernández et al., 2023; López et al., 2023; Navarro et al., 2023). All these elicitation modes can be combined across different levels of the hierarchy, allowing the decision maker to use simpler judgments at higher levels and more detailed assessments where greater discrimination is required.

Table 3 describes the weights used in this work; they aim to reflect plausible relative importance relations within the criteria hierarchy. All intervals were normalized within each node to maintain coherence in the hierarchical aggregation. For example, at the Economic performance node, the weights of capital cost, fixed and variable operation and maintenance, and LCOE were expressed as overlapping intervals reflecting their comparable relevance in cost-based assessments, with the latter retaining a slightly higher central importance. A similar principle was applied at the System relevance and Environmental and health impacts nodes, where intervals reflect the fact that several indicators contribute jointly and none can be assumed to dominate unequivocally.

At the root node, the four main dimensions were weighted using the same rule: their relative importance was derived from the aggregate discriminatory power of their elementary criteria, and then expressed as intervals to reflect uncertainty in cross-dimensional trade-offs.

3.5.2. Preferential thresholds

To avoid overfitting and keep thresholds comparable across heterogeneous units, we define them as fixed fractions of each criterion's observed range in the matrix; that is, thresholds were set as constant fractions of observed dispersion (5%/15%/40% of the range), which allows us to get scale-consistent discrimination without injecting artificial precision. The thresholds required to operationalize the method described in Subsection 3.4 are shown in Table 4. Note how for g_{41}, being defined as an interval criterion, the thresholds are not required to be defined.

3.5.3. Class profiles and ordered categories

Given the nature of the problem, a three-category ordinal scale is appropriate. It allows discrimination without imposing excessive precision and is consistent with exploratory and policy-oriented analyses. The following ordered categories are proposed (Table 5):

Table 3: Criteria weights

Node	Criterion	Weight
Root node	Economic performance	[0.30, 0.45]
	Technical performance	[0.20, 0.35]
	System relevance	[0.15, 0.35]
	Environmental and health impacts	[0.25, 0.40]
Economic performance	Capital cost	[0.20, 0.25]
	Fixed O&M	[0.25, 0.35]
	Variable O&M	[0.25, 0.45]
	LCOE	[0.10, 0.20]
Technical performance	Capacity factor	[1.00, 1.00]
System relevance	Installed capacity	[0.35, 0.45]
	Net generation	[0.40, 0.60]
Environmental and health impacts	Land-use intensity	[0.20, 0.25]
	Deaths/TWh	[0.45, 0.50]
	Life-cycle GHG	[0.30, 0.40]

Table 4: Preferential thresholds

Criterion	Range basis	*q*	*p*	*v*
g_{11}	8937.4−1193.5=7743.9	387.2	1161.6	3097.6
g_{12}	175.0−18.0=157.0	7.9	23.6	62.8
g_{13}	8.99−0.00=8.99	0.45	1.35	3.60
g_{14}	107.5−32.7=74.8	3.74	11.22	29.92
g_{21}	0.93−0.27=0.66	0.03	0.10	0.26
g_{31}	509−80=429	21.5	64.4	171.6
g_{32}	1671−205=1466	73.3	219.9	586.4
g_{42}	24.6−0.22=24.58	1.23	3.69	9.83
g_{43}	970−6 = 964	48.2	144.6	385.6

Table 5: Class profiles and ordered categories

Criterion	r_1 (Non-acceptable)	r_2 (Acceptable)	r_3 (Highly acceptable)
g_{11}	7 500	2 500	1 200
g_{12}	150	40	20
g_{13}	6.0	2.0	0.5
g_{14}	95	40	30
g_{21}	0.30	0.50	0.75
g_{31}	100	150	400
g_{32}	300	600	1 200
g_{42}	[10,20]	[1,5]	[0.2,1]
g_{43}	15	5	1
g_{11}	800	200	50

1. r_1 – Non-acceptable. Technologies that present poor overall performance, typically driven by high costs, low system relevance, or high environmental and health impacts.
2. r_2 – Acceptable. Technologies that exhibit balanced performance, with moderate costs and impacts, but without clear dominance across most criteria.
3. r_3 – Highly acceptable. Technologies with strong overall performance, characterized by low environmental and health impacts, good system relevance, and competitive economic or technical indicators.

The obvious ordering of these classes is:

$$C_1 \prec C_2 \prec C_3$$

For each category, a reference profile (synthetic alternative) is defined. Each profile is constructed using values that are representative of the empirical ranges observed in the performance matrix. For cost and impact criteria, lower values are preferred; for capacity factor, installed capacity, and net generation, higher values are preferred.

4. RESULTS

This section presents the results of the hierarchical multi-criteria sorting procedure applied to the set of electricity generation technologies. Alternatives are evaluated and assigned to ordered classes by considering their performances across all non-elementary criteria of the hierarchy, allowing the analysis to be conducted at different levels of aggregation. This hierarchical perspective enables the identification of strengths and weaknesses of each technology within individual dimensions, as well as their overall classification when all criteria are jointly considered. The results are reported for each aggregation level, highlighting the impact of economic, technical, system-related, and environmental and health dimensions on the final assignments.

4.1. Overall Classification Results

This subsection reports the overall classification results obtained at the overall criterion g_0, where all non-elementary criteria of the hierarchy are jointly considered. Unlike other sorting approaches, the proposed approach may assign an alternative to a range of adjacent classes, reflecting the presence of uncertainty, imprecision, or borderline performance with respect to class profiles.

Recall that $\mathcal{C} = \{C_0, C_1, C_2\}$ denote the ordered set of classes, corresponding to Non-acceptable, Acceptable, and Highly acceptable, respectively, as described in Subsection 3.5.3. For each alternative $a \in A$, the result of the sorting procedure is an assignment interval $[C_k, C_l]$, indicating that the alternative can be assigned to any class between C_k and C_l under admissible preference parameter values. Range-based assignments provide insight into the robustness of the classification results.

Coal is assigned to the range Non-acceptable–Acceptable ($[C_0, C_1]$). This borderline classification is primarily driven by coal's very poor performance on environmental and health criteria, particularly deaths per TWh and life-cycle greenhouse gas emissions, which clearly exceed the thresholds associated with higher acceptability classes. Although coal exhibits strong system relevance, with high installed capacity and net generation, and satisfactory technical characteristics, these strengths are insufficient to robustly compensate for its environmental drawbacks under most admissible weight configurations. Consequently, coal cannot be stably assigned beyond the acceptable class and remains sensitive to the relative importance given to environmental and health impacts.

Natural gas is robustly assigned to the Acceptable class ($[C_1, C_1]$). Its classification is driven by a balanced performance profile: natural gas shows relatively favorable economic indicators and strong system relevance, combined with moderate environmental impacts. While its greenhouse gas emissions and health impacts are significantly lower than those of coal, they remain well above the thresholds required for the Highly acceptable class. At the same time, its performance is consistently superior to the non-acceptable profiles, resulting in a stable intermediate classification.

Nuclear is robustly assigned to the Highly acceptable class ($[C_2, C_2]$). This result is mainly driven by nuclear energy's outstanding performance on environmental and health criteria, particularly very low greenhouse gas emissions and low death rates per unit of electricity generated. In addition, its high capacity factor provides strong technical support for the assignment. Although nuclear exhibits high capital and fixed operating costs, the hierarchical aggregation and the weight ranges allow these economic disadvantages to be outweighed by its favorable environmental and technical characteristics, leading to a stable assignment to the highest class.

Hydropower is assigned to the Acceptable class ($[C_1, C_1]$). Its classification is explained by mixed performance across criteria. Hydropower performs well on environmental and health criteria, with low emissions and death rates, but shows relatively high capital costs and significant land-use intensity. Its moderate system relevance and capacity factor further position it between the lower and upper class profiles. As a result, hydropower does not consistently meet the thresholds required for the Highly acceptable class, but it clearly outperforms the non-acceptable profiles, yielding a robust intermediate assignment.

Wind is robustly assigned to the Highly acceptable class (($[C_2, C_2]$). This assignment is primarily driven by its very favorable environmental and health performance, including extremely low death rates and greenhouse gas emissions, as well as low variable operating costs. Although wind exhibits lower capacity factors and moderate system relevance compared to dispatchable technologies, these limitations are insufficient to offset its strong performance on heavily weighted environmental criteria. Consequently, wind remains in the highest class across all admissible preference configurations.

Solar photovoltaic technology is also robustly assigned to the Highly acceptable class (($[C_2,C_2]$). Similar to wind, this result is driven by very low health impacts and low life-cycle greenhouse gas emissions, combined with low operating costs. While solar PV displays relatively low capacity factors and non-negligible land-use intensity, these aspects do not prevent it from satisfying the profiles associated with the highest acceptability class when the full set of criteria is considered.

4.2. Results at the Economic Performance Level

This subsection analyzes the classification results obtained when alternatives are evaluated exclusively under the economic performance criterion g_1, which aggregates capital cost, fixed operation and maintenance cost, variable operation and maintenance cost, and levelized cost of electricity. At this level, assignments reflect purely cost-related considerations, independently of technical, system-level, or environmental and health impacts.

Coal is assigned to the range Non-acceptable–Acceptable. This classification is primarily driven by its high capital cost and relatively high variable operating costs, which exceed the thresholds associated with the higher acceptability class. Although coal does not consistently fall below all non-acceptable economic profiles, its cost structure prevents a robust classification beyond the acceptable class under most admissible weight combinations. Natural gas is robustly classified as Acceptable. This result is mainly explained by its relatively low capital cost and moderate fixed and variable operating costs. These characteristics allow natural gas to comfortably satisfy the acceptable economic profiles, while its cost performance remains insufficient to meet the most demanding thresholds associated with the highly acceptable class.

Nuclear is classified within the Non-acceptable–Acceptable range at the economic level. This assignment is driven by very high capital and fixed operating costs, which strongly penalize nuclear energy under purely economic considerations. Although its variable operating costs and levelized cost of electricity are comparatively favorable, these advantages are not sufficient to compensate for the large upfront investment requirements, resulting in a borderline economic classification. Hydropower is also assigned to the Non-acceptable–Acceptable range. This outcome is largely explained by high capital costs and non-negligible fixed operating costs, which limit its economic attractiveness despite low variable operating costs. As a result, hydropower does not robustly satisfy the economic thresholds required for higher acceptability.

Wind is robustly assigned to the Highly acceptable class. This classification is driven by its low capital cost, very low fixed and variable operating costs, and competitive levelized cost of electricity. Even when conservative economic weight configurations are considered, wind consistently meets or exceeds the profiles associated with the highest economic acceptability class. Solar photovoltaic technology is also robustly classified as Highly acceptable at the economic level. This result is explained by its low capital cost, minimal operating costs, and favorable levelized cost of electricity. Although its capacity factor is low, this aspect does not influence the economic-level evaluation and therefore does not affect its classification under g_1.

4.3. Results at the Technical Performance Level

This subsection presents the classification results obtained when alternatives are evaluated under the technical performance criterion g_2, which is defined solely by the capacity factor. As g_2 consists of a single elementary criterion, no aggregation is required at this level, and the assignments directly reflect differences in average utilization rates across technologies.

Nuclear is robustly assigned to the Highly acceptable class due to its very high capacity factor, which consistently exceeds the threshold associated with the highest acceptability profile. This result reflects nuclear energy's ability to operate at near-continuous output over extended periods. Coal, natural gas and hydropower are assigned to the Acceptable class. Their capacity factors are sufficient to meet the acceptable technical performance threshold but do not consistently reach the level required for classification as highly acceptable. Finally, wind and solar photovoltaic technologies are assigned to the Non-acceptable class, since their relatively low capacity factors, inherent to variable renewable energy sources, prevent them from meeting the thresholds associated with acceptable or highly acceptable technical performance when capacity factor is considered in isolation.

4.4. Results at the Environmental and Health Impact Level

Here, we present the classification results obtained when alternatives are evaluated exclusively under the environmental and health impact criterion g_4, which aggregates land-use intensity, death rates associated with electricity generation, and life-cycle greenhouse gas emissions. At this level, assignments reflect the non-market externalities of electricity generation technologies, independently of economic costs, technical performance, or system relevance.

For this scenario, coal is robustly assigned to the Non-acceptable class. This result is driven primarily by its very high life-cycle greenhouse gas emissions and its exceptionally high death rate per unit of electricity generated. Even under permissive weight configurations, these impacts consistently exceed the thresholds associated with acceptable performance, leading to a stable classification in the lowest class.

Natural gas is assigned to the Acceptable class. Its classification reflects a substantial improvement over coal in terms of greenhouse gas emissions and health impacts, yet these indicators remain significantly higher than those of low-carbon technologies. Although natural gas exhibits relatively low land-use intensity, this advantage is insufficient to justify classification as highly acceptable when health and climate impacts are considered. Hydropower is also assigned to the Acceptable class. While hydropower performs well in terms of greenhouse gas emissions and death rates, its land-use intensity is relatively high and exhibits substantial variability. This combination results in an intermediate classification, as hydropower does not consistently satisfy the most demanding environmental and health profiles across all admissible parameter values.

Nuclear is robustly assigned to the Highly acceptable class. This classification is driven by very low greenhouse gas emissions and one of the lowest reported death rates per unit of electricity generated. In addition, nuclear energy exhibits extremely low land-use intensity. These characteristics allow nuclear technology to satisfy the highest environmental and health thresholds under all admissible weight configurations. Wind is also classified as Highly acceptable. Its assignment is explained by extremely low death rates and very low life-cycle greenhouse gas emissions, combined with low land-use intensity when considering direct impacts. These favorable characteristics dominate any variability in land-use estimates and lead to a stable classification in the highest class. Finally, solar photovoltaic technology is also robustly assigned to the Highly acceptable class. Despite exhibiting higher land-use intensity than wind and nuclear, solar PV maintains very low death rates and relatively low greenhouse gas emissions. These advantages are sufficient to consistently satisfy the profiles associated with the highest environmental and health acceptability class.

5. CONCLUSION

This paper proposed a hierarchical multi-criteria sorting framework to support the evaluation of electricity generation technologies under multiple, potentially conflicting dimensions. Rather than producing a single ranking, the approach assigns technologies to ordered acceptability classes, providing a decision-oriented perspective that is well suited to policy analysis, investment screening, and strategic planning in the energy sector. The empirical application to major electricity generation technologies in the United States demonstrates the ability of the proposed approach to generate interpretable and robust classifications. Low-carbon technologies, particularly nuclear, wind, and solar photovoltaic, are consistently classified in the highest acceptability class when economic, technical, system-level, and environmental and health criteria are jointly considered. Fossil-based technologies, especially coal, exhibit less favorable and less robust classifications, reflecting the strong influence of environmental and health impacts on overall acceptability. Technologies such as natural gas and hydropower display intermediate classifications, highlighting the presence of trade-offs and sensitivity to preference structures.

A key contribution of the study is the explicit treatment of uncertainty. Range-based class assignments reveal when classifications are robust and when they depend on assumptions regarding criteria importance or performance variability. This feature avoids false precision and provides decision makers with more informative insights than conventional single-score or deterministic ranking approaches. Moreover, the hierarchical structure allows results to be analyzed at different levels of aggregation, supporting nuanced interpretation and facilitating communication with stakeholders.

The proposed framework is subject to several limitations. The analysis is conducted at the technology level and does not capture heterogeneity across individual plants or regional contexts. In addition, the set of criteria is constrained by data availability and does not explicitly include factors such as grid integration costs, market dynamics, or policy instruments. Future research could extend the framework to incorporate plant-level data, dynamic scenarios, or additional financial and regulatory indicators, as well as explore participatory preference elicitation processes involving multiple stakeholders (Diaz et al., 2022; Solares et al., 2022).

The study illustrates how hierarchical multi-criteria sorting can serve as a transparent and flexible decision-support tool for evaluating electricity generation technologies in complex and uncertain environments. By combining rigorous decision analysis with publicly available data, the proposed approach offers a practical contribution to the assessment of energy technologies and supports more informed and responsible decision-making in the context of energy transition.

Several directions for future research emerge from this study. First, the proposed framework could be extended to a plant-level or regional analysis, allowing heterogeneity in technology performance, environmental impacts, and system integration conditions to be explicitly modeled. Second, additional criteria relevant to financial decision-making, such as investment risk, revenue volatility, or exposure to policy and market uncertainty. Third, the framework could be adapted to dynamic and scenario-based settings, enabling the evaluation of technologies under alternative demand, policy, or decarbonization pathways. Finally, future work could explore participatory preference elicitation involving multiple stakeholders, such as policymakers, investors, and system operators, to assess how differing perspectives influence classification outcomes.

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