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Renewable Energy Source Ranking and Analysis Using Fuzzy MCDM, ML, and XAI Techniques

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Abstract. To evaluate renewable energy alternatives under uncertainty, this study develops a hybrid decision support model combining fuzzy MCDM techniques with machine learning based prediction and XAI tools to enhance transparency in energy planning. Six renewable sources were assessed using Fuzzy TOPSIS and Fuzzy ELECTRE across six sustainability-related criteria: cost, efficiency, environmental impact, ease of implementation, technological innovation, and social acceptance. Entropy weighting was used to determine criterion importance. Fuzzy TOPSIS ranked hydropower highest (closeness coefficient = 0.7142) and wave energy lowest (0.3290). Fuzzy ELECTRE clarified dominance relationships among the options. For predictive analysis, machine learning models XGBoost, CatBoost, and Gradient Boosting were trained to forecast MCDM scores. XGBoost outperformed others ($R^2 = 0.9999$, MAE = 0.0003). Explainable AI tools (SHAP and DALEX) revealed environmental impact and efficiency as the most influential factors. This integrated framework supports transparent and data-driven renewable energy planning and can inform sustainable policy decisions.

Keywords: Fuzzy MCDM, TOPSIS, ELECTRE, XGBoost, Explainable AI, Renewable Energy

1 INTRODUCTION

The increasing global urgency to transition from fossil fuels to renewable energy sources has amplified the need for transparent and data-driven decision-making mechanisms in energy planning. Although renewable energy alternatives such as solar, wind, biomass, geothermal, hydroelectric, and wave energy offer substantial environmental and economic benefits, their evaluation involves conflicting criteria and uncertain data (Pandey et al., 2021). Therefore, a structured multi-criteria decision-making (MCDM) approach becomes critical to facilitate objective selection processes under these complex circumstances (Shatnawi et al., 2021).

In recent years, fuzzy MCDM techniques have been widely adopted to handle imprecision and subjectivity in evaluating renewable energy options (Mardani et al., 2015). Among these methods, Fuzzy TOPSIS and Fuzzy ELECTRE have attracted significant attention due to their mathematical robustness and ability to process vague linguistic evaluations (Santi et al., 2015; Ali et al., 2024). While Fuzzy TOPSIS determines the relative closeness of each alternative to the ideal solution, Fuzzy ELECTRE analyses dominance relationships among alternatives, particularly under uncertain or incomplete information conditions. Despite their growing application, current research often focuses solely on ranking performance, overlooking the interpretability and transparency of the decision-making outcomes.

To address this issue, explainable artificial intelligence (XAI) techniques namely SHAP (Shapley Additive Explanations) and DALEX (Descriptive Machine Learning Explanations) have been incorporated into this study. These tools are employed to analyze and visualize the influence of decision criteria on the final scores produced by machine learning models trained to replicate fuzzy MCDM outputs. In doing so, a transparent and interpretable framework is introduced, enabling stakeholders to comprehend the underlying rationale behind the ranking of energy sources.

The central research question of this study is as follows:

RQ: Can the ranking results produced by fuzzy MCDM methods be effectively predicted by machine learning models and explained through SHAP and DALEX to reveal the most influential criteria in renewable energy source evaluation?

Accordingly, the primary objective of this study is to develop an integrated methodological framework that combines fuzzy MCDM techniques with explainable machine learning models to evaluate renewable energy alternatives. Specifically, Fuzzy TOPSIS and Fuzzy ELECTRE are applied to rank energy resources according to entropy-weighted criteria. These scores are then predicted by supervised machine learning models, and the contribution of each criterion to the prediction is examined using SHAP and DALEX, increasing the transparency of these prediction models.

Accordingly, the research objectives are as follows:

- To replicate the ranking results of fuzzy MCDM techniques using machine learning models and explain the underlying decision logic using SHAP and DALEX to increase interpretability.
- To propose an integrated methodological framework that reconciles predictive accuracy with interpretability by jointly generating and explaining energy resource rankings.

- To provide a transparent, auditable, and stakeholder-focused decision support system for sustainable energy planning.

While multi-criteria decision-making (MCDM) techniques have been widely used to address the complexity of energy planning under uncertainty, prior studies have often lacked interpretability and predictive validation. For instance, a comprehensive review highlights the increasing reliance on fuzzy and stochastic MCDM methods in civil and energy-related domains (Antucheviciene et al., 2015; Lee and Chang, 2018). However, these studies also acknowledge key methodological gaps, including the limited ability to provide transparent reasoning behind decisions and the absence of integrated frameworks combining uncertainty modeling with decision traceability. Similarly, Lee and Chang's (2018) comparative analysis, which evaluates renewable energy alternatives for Taiwan using traditional MCDM methods (TOPSIS, ELECTRE, VIKOR, and WSM), offers valuable insights into ranking accuracy and weight sensitivity. Nevertheless, these methods primarily function as black-box mechanisms, offering little visibility into the rationale behind each ranking outcome.

In contrast, the current study advances the literature by proposing an integrated and interpretable decision-support framework that combines entropy-weighted fuzzy MCDM techniques (Fuzzy TOPSIS and Fuzzy ELECTRE) with predictive machine learning models and post-hoc explanation tools such as SHAP and DALEX. This hybrid architecture not only captures the inherent uncertainty in energy decision-making through interval type-2 fuzzy modeling, but also enhances transparency by revealing the influence of each decision criterion on model outputs. By bridging the methodological gap between ranking accuracy and decision interpretability, the proposed approach offers a novel, auditable, and context-aware solution for sustainable energy source evaluation.

The main contributions of this study are as follows:

- A comparative evaluation of Fuzzy TOPSIS and Fuzzy ELECTRE is conducted to analyze their performance across various data structures in renewable energy ranking.
- SHAP and DALEX are employed to interpret the outputs of machine learning models trained on MCDM scores, thereby providing a transparent and explainable decision-support mechanism for energy stakeholders.
- This study contributes to the limited literature on the integration of fuzzy MCDM methods with machine learning and XAI in the energy sector, offering a novel framework for transparent energy policy formulation.
- A unified analytical pipeline is proposed, combining prediction and explanation of MCDM outputs within a single decision framework, thus establishing a new methodological contribution to the literature.

The remainder of this paper is structured as follows: Section 2 reviews the relevant literature on fuzzy MCDM and explainable AI in energy evaluation. Section 3 presents the methodological framework and dataset. Section 4 discusses the empirical findings and interpretation results. Finally, Section 5 concludes the study with key insights, contributions to the literature, and recommendations for future research directions.

2 Related Work

The increasing energy demand and the global transition toward sustainability have intensified research on the comparative evaluation of renewable energy alternatives using fuzzy multi-criteria decision-making (MCDM) methods. Among these, Fuzzy TOPSIS and Fuzzy ELECTRE are two of the most widely adopted techniques due to their robustness in handling ambiguity and multi-dimensional criteria. However, recent literature highlights the need to move beyond method-centric classifications and instead examine how different methods perform under varying data structures, criteria set, and contextual priorities (Pramanik et al., 2021).

2.1 Studies Using Fuzzy TOPSIS and ELECTRE

Numerous reviews have documented the growing application of fuzzy MCDM methods across diverse sectors including energy, transportation, and environmental planning (Mardani et al., 2017). These methods have also been employed in transportation, waste management, and water resource planning. However, the complexity of renewable energy systems—where economic, social, environmental, and policy dimensions interact—makes comparative evaluation particularly challenging, thus increasing the relevance of structured decision models.

Studies using Fuzzy TOPSIS and ELECTRE for renewable energy evaluation generally focus on ranking energy alternatives based on economic, environmental, and technological criteria. While Fuzzy TOPSIS is frequently applied to structured numerical datasets and provides sensitivity to weight changes, Fuzzy ELECTRE is often preferred in scenarios involving qualitative judgments and uncertainty (Chu and Nghiem, 2023; Niu et al., 2020). A key difference lies in their mathematical foundations: TOPSIS is distance based, while ELECTRE is dominance-based. This leads to variations in ranking outcomes, especially when dealing with heterogeneous data or incomplete inputs. Most studies apply these methods independently, with few offering head-to-head comparisons using the same dataset.

For instance, Mousavi-Nasab and Sotoudeh-Anvari (2017) proposed an integrated fuzzy MCDM approach combining fuzzy DEMATEL, fuzzy grey relational analysis, and fuzzy linear programming to solve the sustainable supplier selection problem under imprecise conditions. Although not directly focused on energy, their method demonstrates the flexibility of fuzzy models in managing structured decision problems with quantifiable sustainability criteria. Karayel and Saraoğlu (2021) conducted a comparative analysis of fuzzy TOPSIS and ELECTRE for selecting renewable energy sources in Turkey, showing that each method responds differently to varying uncertainty levels and data structures. Hernández et al. (2020) utilized fuzzy TOPSIS to assess energy alternatives in Turkey, emphasizing social acceptance and innovation using semi-structured surveys. Molnar (2022) contributed to the broader understanding of model transparency by outlining interpretable machine learning techniques such as SHAP and LIME, which complement MCDM approaches when combined with predictive models. Alsaigh et al. (2022), in turn, reviewed interpretable machine learning applications in energy systems and discussed the challenges of making black-box models more transparent, particularly in building energy management contexts (Barredo Arrieta et al., 2020).

These comparative insights reveal that while Fuzzy TOPSIS excels in numerical, well-structured environments, Fuzzy ELECTRE offers advantages under uncertain and mixed-input conditions. Yet, the lack of direct comparative studies using a unified dataset limits methodological benchmarking. This study addresses that gap by applying both methods to the same decision matrix with entropy-based weights.

2.2 Studies Using SHAP and DALEX in Energy Systems

On the other hand, studies employing SHAP and DALEX in the energy domain predominantly focus on interpretability of machine learning models. These works typically involve structured time series or sensor-based datasets, often applying ensemble models such as XGBoost or Random Forest. SHAP is commonly used for global and local feature importance, while DALEX provides additional tools for model auditing and visualization. Additionally, the ability of SHAP and DALEX to visualize and quantify decision pathways adds a critical layer of interpretability that is often missing in classical MCDM frameworks. However, these methods are generally disconnected from MCDM logic and have not been applied to explain fuzzy decision outputs, highlighting a methodological gap in existing literature (Yusuf et al., 2021).

For example, Zhou et al. (2023) used SHAP to identify key meteorological variables in photovoltaic forecasting models. Rafique and Khan (2024) applied DALEX in wind farm site selection using ensemble learning, enhancing transparency. Kumar and Singh (2024) combined SHAP with a fuzzy-based load balancing model in smart grids to improve control-system trust. These efforts demonstrate the growing interest in XAI tools in energy-related decision contexts but still lack integration with fuzzy MCDM frameworks.

2.3 SHAP and DALEX for Explaining MCDM Outcomes

While prior studies have explored SHAP and DALEX for model interpretability, their application to post-hoc explanation of fuzzy MCDM results such as closeness coefficients (TOPSIS) or dominance scores (ELECTRE) has been rarely investigated (Jong and Ahmed, 2024). In this context, SHAP and DALEX are not merely used for explaining machine learning outputs, but rather to quantify how much each original criterion (e.g., cost, efficiency, environmental impact) contributes to the final scores produced by Fuzzy TOPSIS and ELECTRE. This allows for a transparent breakdown of MCDM outcomes, making the decision process both explainable and auditable.

In this study, MCDM scores are modeled using XGBoost, and SHAP/DALEX are applied to interpret how the input criteria influence these scores. This novel integration provides both interpretability and validation, supporting decision-makers in understanding not just what the ranking is, but why it was formed. This responds to growing calls in the literature to enhance explainability in energy-related AI-supported decisions.

2.4 Research Contribution

This study integrates SHAP and DALEX with fuzzy MCDM to enhance transparency in evaluating renewable energy alternatives. While prior research has used XAI in energy contexts, their combined use with fuzzy decision-making remains underexplored.

By quantifying criterion influence, the proposed framework offers a novel, explainable, and auditable approach for renewable energy planning and future decision-critical applications.

3 PROPOSED COMPUTATIONAL FRAMEWORK

To address the complexity and uncertainty inherent in evaluating renewable energy alternatives, this study adopts a structured computational framework. The approach combines fuzzy multi-criteria decision-making (MCDM) techniques with machine learning (ML) and explainable artificial intelligence (XAI) methods to ensure both accuracy and transparency. Initially, Fuzzy TOPSIS and Fuzzy ELECTRE were applied to rank alternatives based on entropy-weighted evaluation criteria.

These MCDM techniques were selected for their capacity to handle imprecise and linguistic information. Subsequently, supervised ML models were trained to predict the MCDM scores, and model interpretability was enhanced using SHAP and DALEX. A visual overview of the methodological flow is presented in Figure 1.

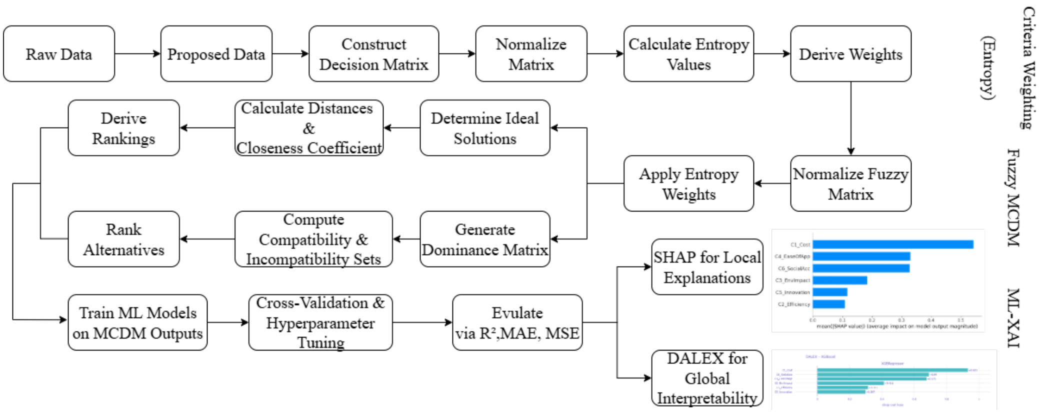


Fig. 1: Workflow of the proposed fuzzy MCDM–ML–XAI integration

3.1 Research Flow and Dataset

Linguistic evaluations of renewable energy alternatives based on six sustainability-related criteria are presented in Table 1. To ensure full transparency and traceability, their application to each alternative is explained in detail in the Interval Type-2 Fuzzy Decision Matrix (Table 2).These qualitative evaluations are derived from a synthesis of peer reviewed articles, technical reports, and official data sources. This specially constructed dataset evaluates six renewable energy alternatives solar, wind, hydro, geothermal, biomass, and wave energy across six decision criteria using linguistic variables. Each criterion is selected to balance the four pillars of sustainable development: environmental, technical, economic, and social factors (Shao et al., 2020). The relevance of these criteria has been validated by prior studies and global frameworks such as the UN Sustainable Development Goals and IEA strategic energy reports.

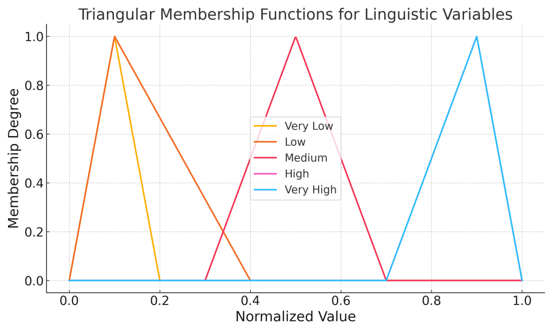
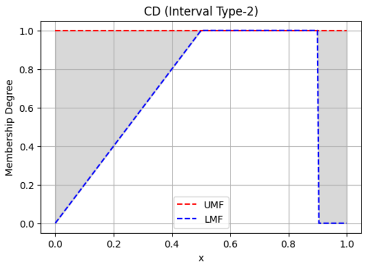


Fig. 2: Membership functions of linguistic variables represented as Triangular Fuzzy Numbers (TFNs).

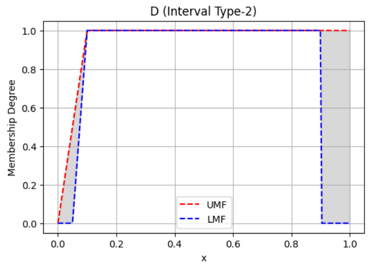
Table 1: Comparison of Renewable Energy Types by Key Criteria

Type	**Cost**	**Eff.**	**Env. Impact**	**Ease**	**Tech. Innov.**	**Soc. Acc.**
Solar	Low	Low	Very Low	Very High	High	Very High
Wind	Low	Medium	Low	High	Medium	High
Biomass	High	Medium	High	Medium	Low	Low
Geothermal	Medium	Low	Medium	Low	Medium	Medium
Hydroelectric	Medium	Very High	Very High	Low	Very Low	Very High
Wave	Very High	Low	Low	Very Low	Very High	Medium

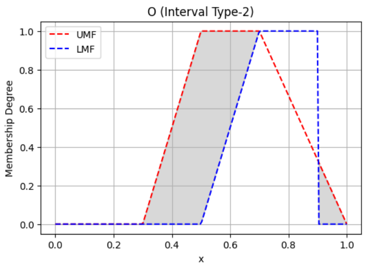
To operationalize the linguistic assessments in a mathematical framework, a standardized set of linguistic terms (Very Low, Low, Medium, High, and Very High) was used. These terms were chosen due to their wide acceptance in the fuzzy decision-making literature and their ability to reflect imprecise human judgments (Zadeh, 1975). Each term was then mapped to a corresponding Triangular Fuzzy Number (TFN) based on predefined membership functions. The membership function graphs of the linguistic variables are provided in Figure2. To better account for expert-based uncertainty and subjectivity, TFNs were extended to Interval Type-2 Fuzzy Numbers (IT2 FNs) by incorporating binary evaluations from distinct expert profiles (Kahraman et al., 2015). This improved representation supports more detailed modeling of uncertainty in sustainability related evaluations. The final decision matrix containing IT2 FNs for all alternatives and criteria is presented in Table2



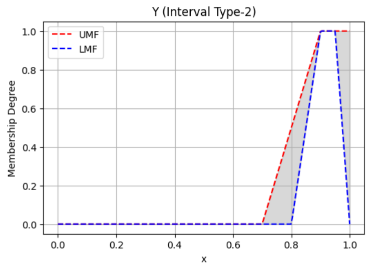
(a) Very Low



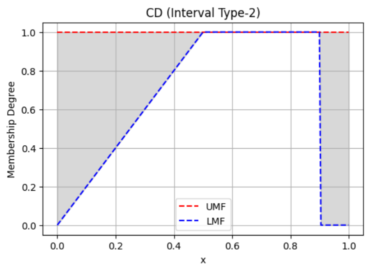
(b) Low



(c) Medium



(d) High



(e) Very High

Fig. 3: Workflow illustrations for different fuzzy MCDM–ML–XAI scenarios.

Table 2: Interval Type-2 Fuzzy Decision Matrix for renewable energy alternatives.

Alternative	**Cost (C1)**	**Efficiency (C2)**	**Environmental Impact (C3)**	**Ease of Impl. (C4)**	**Tech. Innov. (C5)**	**Soc. Acc. (C6)**
Solar	(0.0, 0.1, 0.4)	(0.0, 0.1, 0.4)	(0.0, 0.1, 0.2)	(0.7, 0.9, 1.0)	(0.7, 0.9, 1.0)	(0.7, 0.9, 1.0)
Wind	(0.0, 0.1, 0.4)	(0.3, 0.5, 0.7)	(0.0, 0.1, 0.2)	(0.5, 0.7, 0.9)	(0.3, 0.5, 0.7)	(0.7, 0.9, 1.0)
Biomass	(0.7, 0.9, 1.0)	(0.3, 0.5, 0.7)	(0.7, 0.9, 1.0)	(0.3, 0.5, 0.7)	(0.0, 0.1, 0.4)	(0.0, 0.1, 0.4)
Geothermal	(0.3, 0.5, 0.7)	(0.0, 0.1, 0.4)	(0.3, 0.5, 0.7)	(0.1, 0.3, 0.5)	(0.3, 0.5, 0.7)	(0.3, 0.5, 0.7)
Hydroelectric	(0.3, 0.5, 0.7)	(0.7, 0.9, 1.0)	(0.7, 0.9, 1.0)	(0.0, 0.1, 0.4)	(0.7, 0.9, 1.0)	(0.7, 0.9, 1.0)
Wave	(0.9, 1.0, 1.0)	(0.0, 0.1, 0.4)	(0.0, 0.1, 0.2)	(0.7, 0.9, 1.0)	(0.0, 0.1, 0.2)	(0.3, 0.5, 0.7)

3.2 Criteria Definition and Entropy Weights

The entropy weighting method was chosen to calculate the relative importance of the evaluation criteria due to both the structure of the dataset and the nature of the criteria involved.

The criteria used in the study Cost, Efficiency, Environmental Impact, Ease of Implementation, Technological Innovation, and Social Acceptance represent a diverse set of factors blending quantitative and qualitative dimensions. While some criteria, such as Cost and Efficiency, can be approximated numerically, others, such as Ease of Implementation and Social Acceptance, are more interpretative and context sensitive. Given this mixed structure, entropy provides a transparent and objective framework to determine which criteria have greater impact based solely on their observed variation among alternatives (Garg et al., 2015). This approach ensures that the weighting process is data driven and reproducible and avoids potential bias introduced by subjective weighting schemes. It also supports the study's aim of creating a fair and explainable decision model.

To begin with, a decision matrix $\tilde{x}_{ij}$ was created based on fuzzy evaluations of six renewable energy alternatives according to six sustainability related criteria. To eliminate scale effects, the matrix was scaled proportionally by each entry according to their column totals to create a normalized decision matrix x^*_{ij}. The entropy value for each criterion was then calculated using Equation 1:

$$e_j = -\frac{1}{\ln m} \sum_{i=1}^{m} x^*_{ij} \ln x^*_{ij} \tag{1}$$

This formulation is based on the classical entropy weight method as described by Garg et al. (2015). Following the entropy calculation, the degree of divergence for each criterion was computed as $d_j = 1 - e_j$, indicating the criterion's ability to differentiate between alternatives. A higher d_j implies greater discriminative power. Finally, the normalized weight of the criteria was obtained using Equation 2:

$$w_j = \frac{d_j}{\sum_{j=1}^{n} d_j} \tag{2}$$

The normalized weights are computed according to the entropy-based divergence measure, also following the method of Garg et al. (2015).

3.3 Fuzzy TOPSIS Procedure

To rank renewable energy alternatives under uncertainty and ambiguity, this study uses the Fuzzy TOPSIS method extended with Interval Type-2 Fuzzy Numbers (IT2 FNs) to better handle linguistic and imprecise data (Yucesan et al., 2019). This method is particularly well-suited for sustainability assessments, where both qualitative and quantitative factors coexist and evaluations often rely on subjective expert judgments (Ezhilarasan and Vijayalakshmi, 2020).

The decision matrix used in this stage consists of six alternatives and six assessment criteria. Each criterion value is represented as an IT2 FN reflecting linguistic assessments such as Low, Medium, and High, which are initially derived from expert informed literature sources and then converted into fuzzy numbers. This structure allows for a more robust modeling of uncertainty and variability found in the assessment of renewable energy systems.

The entropy based weights calculated in the previous step are directly integrated into the Fuzzy TOPSIS algorithm to provide an objective weighting scheme. These weights proportionally adjust the impact of each criterion in subsequent calculations.

In the fuzzy TOPSIS procedure, first the fuzzy decision matrix is normalized. The normalized fuzzy values are multiplied by the entropy derived weights, preserving both the fuzziness and the objective importance. Then, the fuzzy positive ideal solution (FPIS) and fuzzy negative ideal solution (FNIS) are determined using Equation 3.

$$d_i^* = \sum_{j=1}^{n} d(\tilde{v}_{ij}, \tilde{v}_j^*), \quad d_i^- = \sum_{j=1}^{n} d(\tilde{v}_{ij}, \tilde{v}_j^-) \tag{3}$$

The distance of each alternative to FPIS and FNIS is calculated using a fuzzy distance metric (e.g., the vertex method or Euclidean distance adapted to IT2 FNs). Finally, a proximity coefficient indicating the relative proximity of each alternative to the ideal solution is calculated according to Equation 4. The alternatives are ranked according to their decreasing proximity values.

$$CC_i = \frac{d_i^-}{d_i^* + d_i^-} \tag{4}$$

This method effectively combines the linguistic flexibility of fuzzy logic with a rigorous and explainable ranking process, enabling transparent evaluation of energy alternatives in the presence of subjective judgments and data driven weightings.

3.4 Fuzzy ELECTRE Procedure

To complement the TOPSIS-based assessment, this study employs the Fuzzy ELECTRE method, a dominance-oriented multi-criteria decision-making approach enhanced with Interval Type-2 Fuzzy Numbers (IT2 FNs) to effectively model uncertainty and subjectivity in expert evaluations. Unlike compensatory methods, ELECTRE captures pairwise dominance and incomparability, making it suitable for decision problems involving conflicting and imprecise criteria (Taherdoost and Madanchian, 2023).

The decision matrix constructed from linguistic evaluations across six sustainability-related criteria was paired with entropy-based weights to ensure objectivity in comparisons. While Fuzzy TOPSIS ranks alternatives by closeness to an ideal, ELECTRE highlights cases where alternatives partially dominate, are indifferent, or are incomparable, providing deeper insight into the structure of trade offs (Alper and Başdar, 2017).

Given the mixed and partially contradictory nature of the dataset, ELECTRE offers a complementary, relation based perspective that enhances decision transparency and supports more nuanced interpretation in renewable energy planning.

In the application of the Fuzzy ELECTRE method, the process starts with the construction of a fuzzy decision matrix using interval type-2 fuzzy assessments derived from expert-informed literature. These assessments reflect both qualitative and quantitative aspects of six renewable energy alternatives across six sustainability based criteria. In the second step, the decision matrix is normalized and combined with entropy-based weights to form a weighted normalized matrix to ensure comparability and objectivity.

Pairwise comparisons are then made to calculate the concordance and incongruence sets for each alternative; these sets measure the extent to which one alternative dominates the other on certain criteria. These sets are then summed to form fuzzy dominance indices for all pairs of alternatives Equation 5. A threshold value is calculated based on the average dominance strength and is used to construct pairwise dominance matrices Table 3, Table 4 that capture the effective concordance and incongruence relationships Equation 6.

$$\tilde{I}_{k,j} = \sum_{j \in S_{k,j}} \bar{w}_j \tag{5}$$

$$\bar{I} = \frac{1}{n(n-1)} \sum_{k=1}^{n} \sum_{\ell=1}^{n} \tilde{I}_{k,\ell} \tag{6}$$

Table 3: Concordance Matrix

	A1	A2	A3	A4	A5	A6
A1	0.000	0.820	0.820	0.820	0.675	0.675
A2	0.355	0.000	1.000	0.655	0.510	0.855
A3	0.180	0.345	0.000	0.510	0.000	0.690
A4	0.345	0.655	1.000	0.000	0.165	0.855
A5	0.500	0.830	1.000	0.835	0.000	1.000
A6	0.325	0.490	0.660	0.315	0.310	0.000

Finally, the effective dominance matrix is obtained by combining the concordance and incongruence matrices Equation 7. This allows the identification of dominant, indifferent, or incomparable relationships among alternatives and forms the basis for the final ranking. This process enhances the robustness of the evaluation by capturing non-compensatory, asymmetric, and uncertain relationships among energy options.

Table 4: Discrepancy Matrix

	A1	A2	A3	A4	A5	A6
A1	0.00000000	0.15124047	0.15124047	0.85702932	0.90744281	0.15124047
A2	0.45940980	0.00000000	0.00000000	0.70578885	0.75620234	0.53597809
A3	0.88049487	0.83157849	0.00000000	0.70578885	0.75620234	0.65083054
A4	0.88049487	0.83157849	0.00000000	0.00000000	0.53597809	0.53597809
A5	0.73374572	0.68482934	0.00000000	0.03713664	0.00000000	0.00000000
A6	1.00000000	1.00000000	0.83333333	0.83333333	1.00000000	0.00000000

$$f_{k,j} = \begin{cases} 1, & \text{if } \tilde{I}_{k,j} \geq \bar{I} \\ 0, & \text{otherwise} \end{cases} \quad , \quad h_{k,j} = f_{k,j} \otimes g_{k,j} \tag{7}$$

3.5 Machine Learning Models and Settings

To estimate the decision scores produced by the Fuzzy TOPSIS and Fuzzy ELECTRE methods, this study used a set of advanced gradient boosting algorithms known for their accuracy and ability to model nonlinear relationships. Among these, Extreme Gradient Boosting (XGBoost) was selected due to its proven robustness in handling high-dimensional inputs and its built-in regularization capabilities, which help reduce overfitting (Chen and Guestrin, 2016); this is especially valuable in datasets where decision criteria interact in complex ways. LightGBM was integrated into the modeling pipeline to further increase training speed and memory efficiency, especially in larger input domains (Ke et al., 2017). Its leaf-wise tree growth strategy enables deeper exploration of feature interactions, which aligns well with the multi criteria structure of the dataset.

Considering that some of the evaluation features are derived from linguistic variables, the inclusion of CatBoost provided an advantage in capturing latent categorical patterns without requiring extensive preprocessing. The sequential boosting mechanism also supports model stability, which is essential for downstream explainability. In addition to these state of-the art techniques, classical Gradient Boosting and AdaBoost were used to benchmark performance and examine the trade off between simplicity and model expressiveness. Gradient Boosting offers a modular and flexible modeling approach, while AdaBoost provides valuable interpretability, especially under less complex, near-linear data conditions (Bahad and Saxena, 2020). Additionally, Histogram-Based Gradient Boosting was considered due to its fast training capabilities via histogram-based splitting, which is effective when working with numerical approximations of fuzzy data.

All models were trained using k-fold cross-validation and their hyperparameters (such as learning rate, maximum depth, and number of predictors) were tuned via grid search. Performance was evaluated using standard regression metrics, including R^2, Mean Absolute Error (MAE), and Mean Squared Error (MSE).

3.6 Explainable AI Approach (SHAP, DALEX)

To enhance the transparency and interpretability of the predictive models developed in this study, a set of explainable artificial intelligence (XAI) techniques was employed. While gradient boosting algorithms such as XGBoost, LightGBM, and CatBoost offer high predictive accuracy, they are often regarded as black-box models due to their complex internal structures. In decision-making contexts, particularly those involving sustainability and public policy, understanding how a model arrives at its predictions is as important as the predictions themselves.

To address this need, two complementary XAI frameworks were utilized: SHAP (Shapley Additive Explanations) and DALEX (Descriptive Machine Learning Explanations). SHAP provides a game theoretic foundation for quantifying the contribution of each input feature to individual predictions, allowing for local interpretability (Lundberg and Lee, 2017). This made it possible to identify which criteria (e.g., cost, environmental impact, social acceptance) most strongly influenced the predicted scores of specific renewable energy alternatives.

In parallel, DALEX was used to generate global model explanations, such as feature importance rankings and accumulated local effect (ALE) plots. These visual tools helped reveal the overall structure and behavior of each model across the entire dataset. Together, SHAP and DALEX offered both fine grained and holistic insights, ensuring that the models remained transparent and aligned with the principles of fair and accountable decision support (Baniecki et al., 2021).

The integration of XAI techniques not only facilitated model diagnostics and validation, but also reinforced trust in the model outputs an essential factor when supporting high stakes decisions such as renewable energy investment planning.

4 ANALYSIS AND RESULTS

It is not enough to just rank renewable energy alternatives; the logic behind these rankings must also be made visible. For this purpose, the decision scores obtained with Fuzzy TOPSIS and ELECTRE methods were predicted with different machine learning algorithms and interpreted in detail with explainable artificial intelligence techniques. The findings reveal the potential to increase both the accuracy and transparency of decision support systems.

4.1 Fuzzy TOPSIS Rankings

In the analysis conducted with the Fuzzy TOPSIS method, the proximity of each alternative to the ideal solution was expressed numerically Table 5. According to the results, hydroelectric energy stands out as the strongest candidate with a proximity coefficient of 0.7142. This is followed by solar (0.6676) and wind energy (0.6206), and these three sources can be considered as priority options for sustainable energy investments.

While geothermal energy (0.5824) exhibited a medium level performance, biomass (0.4294) and especially wave energy (0.3290) were at the end of the list with low scores. This distribution shows that TOPSIS offers a meaningful and consistent ranking among

Table 5: Fuzzy TOPSIS method results

Alternative	**Ci Value**
Solar Energy	0.6676
Wind Energy	0.6206
Biomass Energy	0.4294
Geothermal Energy	0.5824
Hydroelectric Energy	0.7142
Wave Energy	0.3290

the alternatives based on the principle of proximity to the ideal solution. The results obtained facilitate balanced decisions in energy planning from both environmental and economic perspectives.

4.2 Fuzzy ELECTRE Dominance Scores

The Fuzzy ELECTRE method offers a different perspective on multi-criteria decision problems by revealing not only the ranking but also the dominance relationships among the alternatives Table 6. According to the results obtained, hydroelectric and solar energy are the most dominant options with dominance scores of 3.0. Wind and geothermal energy were able to leave only one alternative behind. Biomass and wave energy remained in the weakest position, not being able to dominate any alternative.

Table 6: Dominance numbers of alternatives (ELECTRE results)

Alternative	**Dominance Number**
Solar	3.0
Wind	1.0
Biomass	0.0
Geothermal	1.0
Hydroelectric	3.0
Wave	0.0

This ranking reflects the power of ELECTRE to reveal the prominent relationships in multi-criteria decision environments. The method makes an important contribution in terms of showing which options are more dominant than others, especially in cases where there are conflicting or ambiguous criteria.

4.3 ML Prediction Performance

The accuracy of Fuzzy TOPSIS and ELECTRE scores obtained from decision models has been tested with various machine learning algorithms. In particular, tree-based boosting methods such as XGBoost, CatBoost, and GradientBoost have stood out with their high success rates. These models were able to predict multi-criteria decision data with very low error rates and their overall accuracy was at the level of $R^2 \approx 1$.

While CatBoost and XGBoost showed almost perfect performance in predicting Fuzzy TOPSIS scores ($R^2 = 1.0000$ and 0.9999, respectively), GradientBoost also attracted attention as a strong alternative. On the other hand, LightGBM and HistGradientBoost achieved relatively lower success under limited data conditions. AdaBoost showed the lowest performance with higher error rates in both methods (see Table 7).

Table 7: Performance of machine learning models for Fuzzy TOPSIS

Model	**R²**	**MAE**	**MSE**
XGBoost	0.9999	0.0003	0.0000
LightGBM	0.9749	0.0076	0.0001
CatBoost	1.0000	0.0003	0.0000
AdaBoost	0.9165	0.0146	0.0003
GradientBoost	0.9987	0.0016	0.0000
HistGradientBoost	0.9810	0.0069	0.0001

A similar picture was observed in Fuzzy ELECTRE scores Table 8. XGBoost and CatBoost provided high compliance despite ELECTRE's more complex and ranking-based structure, while AdaBoost was inadequate in modeling this structure.

Table 8: Performance of machine learning models for Fuzzy ELECTRE

Model	**R²**	**MAE**	**MSE**
XGBoost	1.0000	0.0005	0.0000
LightGBM	0.9495	0.1883	0.0631
CatBoost	0.9999	0.0100	0.0002
AdaBoost	0.9021	0.2991	0.1223
GradientBoost	0.9975	0.0432	0.0031
HistGradientBoost	0.9552	0.1825	0.0559

These findings show that gradient boosting models in particular provide generalizable, consistent and reliable estimates on both proximity-based (TOPSIS) and dominance-based (ELECTRE) multi criteria decision data. This makes them extremely suitable for integration with explainable decision support systems.

It should be noted that some machine learning models appear as an average square error (MSE) values, especially for XGboost and Catboost, as absolute resets in Table 5 and 6 (i.e. 0.0000). This is not an anomaly, but rather the result of extremely low error values obtained due to the adaptation of the proximity provided by these models. When the actual MSE values are in the range of 10^{-6} or smaller, they turn into four decimal places during formatting, which causes a value shown 0.0000. Therefore, zero MSE values reflect high model sensitivity rather than any calculation problem or excessive stuck.

4.4 XAI Findings on Criterion Impact

Not only making accurate predictions, but also explaining how these predictions are formed is of great importance in decision support systems. In this study, the internal logic behind model decisions was analyzed with explainable artificial intelligence (XAI) tools such as SHAP and DALEX, focusing on the XGBoost model that provides the highest accuracy.

SHAP analysis of fuzzy TOPSIS scores showed that decisions were determined mainly by environmental impact (C3) and efficiency (C2) criteria. These two criteria provided the highest contribution in terms of both average effect size and precision in model predictions. SHAP values revealed that criteria such as social acceptance (C6) and cost (C1) were also moderately effective in the model, while factors such as ease of implementation (C4) and technological innovation (C5) played a relatively lesser role Figure 4.

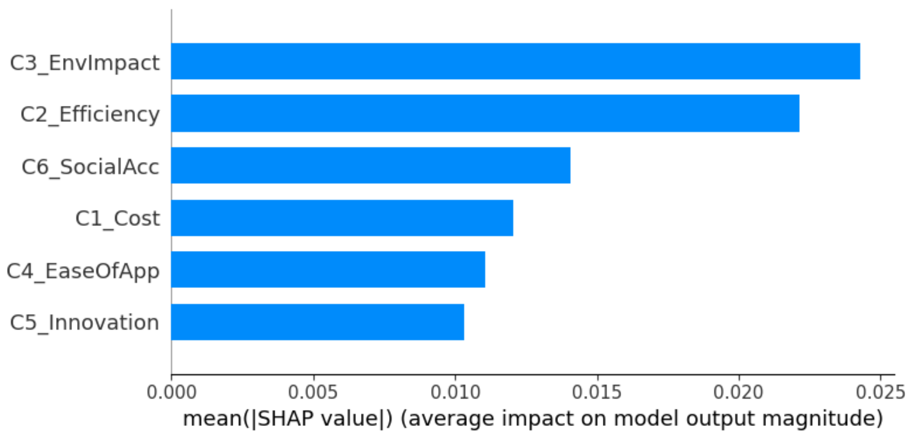


Fig. 4: Feature importance based on SHAP values for the XGBoost model using Fuzzy TOPSIS

A similar order was observed in the DALEX analysis, but it was observed that technological innovation and cost criteria in particular had a close effect on each other. This consistency of SHAP and DALEX contributes to the understanding of the decision-making mechanism of the model at both local and general levels Figure 5.

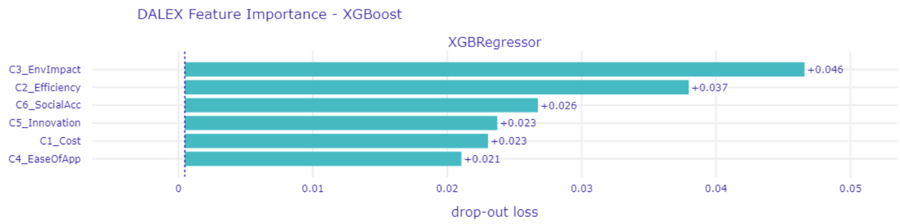


Fig. 5: Feature importance based on SHAP values for the XGBoost model using Fuzzy TOPSIS

On the other hand, a significant change was observed in the analyses of Fuzzy ELECTRE scores. In both SHAP (Figure 6) and DALEX (Figure 7) analyses, the cost (C1) criterion stood out as the most dominant factor by far. This was followed by the ease of implementation (C4) and social acceptance (C6) criteria. Performance-oriented criteria such as environmental impact (C3) and efficiency (C2) remained of secondary importance in this method. This situation is directly related to the structure of the ELECTRE method, which is based on dominance relations instead of ranking.

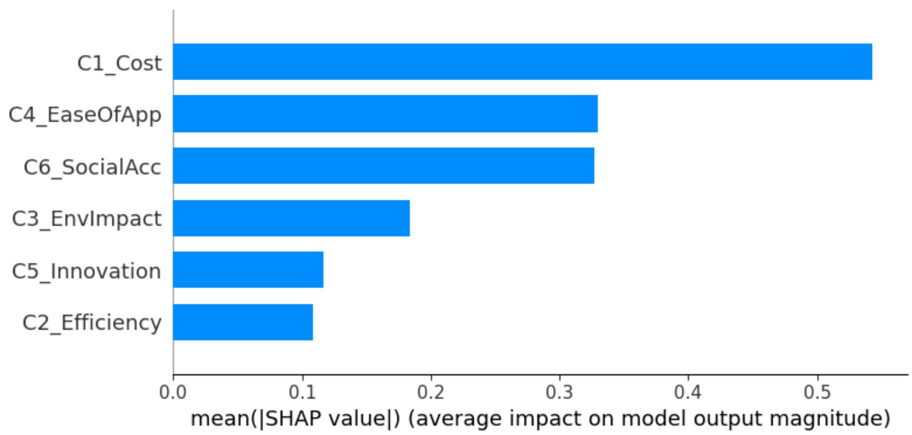


Fig. 6: Feature importance based on SHAP values for the XGBoost model (Fuzzy ELECTRE)

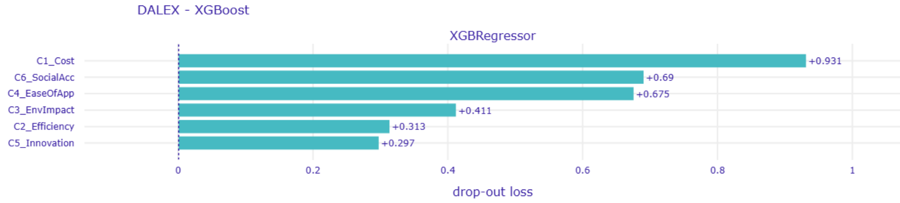


Fig. 7: Global feature importance (drop-out loss) for the XGBoost model using DALEX (Fuzzy ELECTRE)

In addition, in the DALEX analysis, it was observed that the greatest increase in the error rate of the model occurred when the C1 cost criterion was removed; this once again confirmed the decisiveness of the criterion on the decision.

All these findings show that the method used in decision models can change not only the results, but also the hierarchy of impact of the criteria. The integration of XAI tools such as SHAP and DALEX not only increased the model performance; It has also created a reliable basis for sustainable energy policies by making decision-making processes more transparent and auditable.

5 DISCUSSION

Building on the results, this section discusses how renewable energy alternatives were ranked by different decision-making models and interprets the key factors behind these rankings using explainable artificial intelligence techniques.

Hydroelectric energy was identified as the most suitable alternative by both Fuzzy TOPSIS (CC = 0.7142) and Fuzzy ELECTRE (dominance = 3.0), which aligns with the findings of Iqbal et al. (2023) and Kalbar et al. (2013), emphasizing hydro's consistent performance across multiple criteria. Its strong performance can be attributed to high efficiency, social acceptance, and relatively low environmental emissions per kWh. This result contrasts with the findings of Zhang et al. (2021) and Li et al. (2022), where solar energy was often ranked higher due to its affordability and innovation potential. The discrepancy likely stems from the weight structure in our study particularly the emphasis on "Ease of Implementation" and "Environmental Impact" as well as the use of Interval Type-2 Fuzzy modeling, which more effectively captures nuanced uncertainty.

Unexpectedly, wave energy ranked lowest in both methods (TOPSIS CC = 0.3290, ELECTRE dominance = 0.0), despite recent studies highlighting its innovation potential (Amini and McDonald, 2020). This underperformance is likely due to undeveloped infrastructure and high costs (LCOE up to \$0.87/kWh) that outweighed its technological appeal in the overall evaluation (Ke et al., 2017).

SHAP and DALEX analyses yielded clear and transparent insights into which criteria most heavily influenced the rankings. In the Fuzzy TOPSIS + XGBoost model, "Environmental Impact" and "Efficiency" emerged as the most influential features, with global SHAP values of 0.024 and 0.021, respectively. This finding is consistent with Salcedo Sanz et al. (2019), who emphasize the importance of environmental and performance-related attributes in evaluating innovative sources such as wave energy.

In contrast, in the Fuzzy ELECTRE + XGBoost model, “Cost” and “Ease of Implementation” dominated, with SHAP values of 0.54 and 0.32. This mirrors the findings of Karayel and Saraoğlu (2021), where economic feasibility frequently superseded environmental priorities.

Moreover, the 2022 IEA Levelized Cost of Energy (LCOE) report indicates that many renewable technologies particularly solar and wind have achieved cost levels comparable to conventional fossil fuels. This supports the SHAP driven observation that “Cost” is a critical decision factor and provides essential context for its prominence in our ELECTRE based model (International Energy Agency, 2022).

A comparative analysis between Fuzzy TOPSIS and ELECTRE revealed both consistencies and divergences. Hydroelectric energy ranked highest in both methods, indicating strong multi criteria performance. However, differences emerged among the middle ranked alternatives: solar energy ranked second in TOPSIS (CC = 0.6676) and tied with hydroelectric energy in ELECTRE (dominance = 3.0), while wind and geothermal sources were demoted to lower ranks (dominance = 1.0 each) in ELECTRE. This variation can be attributed to methodological differences: TOPSIS favors proximity to an ideal solution, whereas ELECTRE emphasizes pairwise dominance relationships, which can lead to reordering in marginal cases. These findings highlight the sensitivity of MCDM outputs to the internal logic of each method and emphasize the importance of using multiple models for robust decision support.

Among the tested machine learning models, XGBoost consistently achieved superior predictive performance. Its success stems from its ability to handle high dimensional, small scale datasets while using regularization to avoid overfitting. The Interval Type-2 fuzzy structure in our dataset involved nonlinear, overlapping criteria an area where XGBoost’s second order optimization and pruning strategies excelled. SHAP analysis further revealed that “Environmental Impact” and “Cost” exerted asymmetric and nonlinear effects, something that XGBoost captured more effectively than models like AdaBoost or histogram based learners. These strengths explain XGBoost’s low prediction error and consistent interpretability across both decision frameworks (Singh and Nagahara, 2024).

The relationship between SHAP and DALEX results further reinforces the model’s transparency. SHAP highlighted local (instance level) contributions, while DALEX captured global feature behavior via dropout loss. Interestingly, both approaches consistently identified “Environmental Impact” and “Cost” as dominant features across MCDM scenarios. In the Fuzzy TOPSIS model, “Environmental Impact” was emphasized by both SHAP and DALEX. In the ELECTRE based model, both tools highlighted “Cost” and “Ease of Implementation.” These overlaps indicate that local feature importance identified by SHAP is statistically corroborated by DALEX, creating a robust and trustworthy interpretability layer for decision-makers (Alsaigh et al., 2022).

The fact that “Environmental Impact” received the highest SHAP value carries strategic implications for energy planning. It signals a growing societal and regulatory prioritization of sustainability. For policymakers, this suggests that low-emission and ecologically responsible solutions should be prioritized, even if they are not the cheapest or most efficient options. In this context, hydroelectric and solar energy gain strategic weight. The findings also imply that technologies with high efficiency but poor environmental profiles may be deprioritized. Thus, environmental sustainability is no longer a supporting metric; it has become a central decision driver in energy planning.

This study contributes to the literature by integrating fuzzy MCDM models with explainable AI (XAI) methods (Zhao and Wang, 2023). Unlike traditional approaches that merely produce rankings, the proposed hybrid framework also interprets the rationale behind model decisions, offering greater transparency and accountability for high-stakes applications such as renewable energy investment (see Iqbal et al., 2022; Kömürcü et al., 2023).

In response to the research question "Can the ranking results produced by fuzzy MCDM methods be effectively predicted by machine learning models and explained through SHAP and DALEX to reveal the most influential criteria in renewable energy source evaluation?" the findings of this study provide a clear affirmative. The XGBoost based models achieved high predictive accuracy in replicating the fuzzy MCDM outcomes, demonstrating their capacity to approximate complex decision structures. Furthermore, the integration of SHAP and DALEX enabled a nuanced interpretability layer: SHAP clarified instance-level contributions, while DALEX provided global insights into feature behavior. Both tools consistently identified the dominant criteria aligned with the observed rankings such as "Environmental Impact" in Fuzzy TOPSIS and "Cost" in Fuzzy ELECTRE. This convergence not only validates the explainability framework but also confirms that machine learning models, when paired with appropriate XAI tools, can effectively support and elucidate the logic of fuzzy MCDM rankings in the context of renewable energy evaluation.

Despite its methodological strengths, this study has certain limitations that may affect the generalizability of its findings. First, the analysis is based on a predefined set of criteria and alternatives, which may not reflect evolving regional or national priorities. Second, the fuzzy MCDM and XAI models used are sensitive to input design; changes in fuzzification method, weighting, or feature encoding could influence results. The dataset itself was limited in temporal granularity and geographic scope. Moreover, while XGBoost performed well in accuracy, it may fail to detect complex causal relationships that more dynamic or deep learning models could reveal. Future work could expand the dataset, include real time data sources, and explore ensemble XAI models to improve both internal and external validity.

6 CONCLUSION

In this study, a hybrid decision support framework was developed by integrating fuzzy multi criteria decision making (Fuzzy TOPSIS and Fuzzy ELECTRE), entropy based weighting, and explainable machine learning techniques to evaluate renewable energy alternatives under uncertainty. The methodology followed a multi stage approach: linguistic expert assessments were modeled using interval type-2 fuzzy numbers, criteria weights were objectively calculated using the entropy method, and two fuzzy MCDM techniques were applied to rank six energy alternatives. The resulting scores were then predicted using state of the art machine learning models, with XGBoost showing the highest accuracy. Finally, the contribution of each criterion to the decision outcomes was interpreted using SHAP and DALEX, enhancing both transparency and trust in the process.

The results indicate that hydroelectric energy consistently ranked highest across both decision models, while wave and biomass energy alternatives performed poorly. Environmental impact, efficiency, and cost emerged as the most decisive criteria, depending on the method applied. This study contributes to the literature by not only combining robust MCDM and ML models but also incorporating explainability through XAI, allowing stakeholders to understand why a decision is made not just what it is. The proposed framework offers practical value for policymakers and energy planners seeking auditable and transparent tools.

To operationalize the proposed framework in real world settings, a structured implementation roadmap is recommended. Initially, relevant datasets—such as meteorological records, economic indicators, and regional energy consumption statistics—should be consolidated into a centralized and secure database infrastructure. Subsequently, rigorous data preprocessing procedures, including the imputation of missing values, normalization of measurement scales, and correction of class imbalances, must be applied to ensure high data integrity. The hybrid Fuzzy MCDM ML model should then be trained and validated using region-specific parameters to reflect localized priorities and policy objectives. Once validated, the decision-support system should be deployed through an accessible and user oriented software platform, enabling stakeholders to simulate multiple policy scenarios and evaluate the projected impacts of alternative strategies. Finally, a continuous monitoring and adaptive feedback mechanism should be integrated to update model parameters based on new data, thereby ensuring sustained relevance and adaptability under evolving environmental and policy conditions.

Future work may extend the framework with real time data streams, additional energy alternatives, stakeholder-specific preferences, time dependent criteria weights, and more sophisticated learning architectures such as deep learning or ensemble XAI approaches to further enhance predictive performance and decision transparency.

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