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A Hybrid Deep Learning-Driven Stochastic MCDM Framework for Uncertainty-Aware Renewable Energy Resource Selection

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ABSTRACT

Renewable energy source selection is a difficult decision for policymakers due to the high level of uncertainty associated with it, along with the technical factors that accompany it. Most Multi-Criteria Decision Making (MCDM) techniques are based on fixed input parameters or the opinions of experts, which do not account for the predictive uncertainties inherent in energy production data. This research aims to provide a more effective, efficient, and robust framework for the selection of the best mix of renewable energy sources for the future. A five-phase methodology is proposed for this purpose, where the first phase involves the application of the Subjective-Objective Median-based Importance Technique (SOMIT) for the calculation of the weights of the decision criteria. In the second phase, a Multi-Layer Perceptron (MLP) neural network is designed for the prediction of the technical efficiency of solar, wind, biomass, and geothermal energy. Third, the absolute error residuals are monitored for the development of the ANN Uncertainty Criterion. In the fourth phase, the triple validation of the uncertainty-aware data is performed through the application of the MCDM engine, which is based on the TOPSIS, PROMETHEE II, and RAWEC algorithms. In the fifth phase, sensitivity analysis is performed, followed by the Monte Carlo Simulation for testing the robustness of the framework. The results from applying the proposed framework show a clear change in preference. For Türkiye's 2053 net zero target, solar energy is now considered the best future energy source, with a preference score of 0.685. This is higher than wind energy, which most decision-makers previously favored because of its capacity factor. Thus, the proposed framework is more effective, efficient, and robust, as indicated by the Monte Carlo Simulation results, where the results obtained from the application of the proposed framework were stable for 92.4% of the scenarios.

1. Introduction

The global energy system is changing. IEA [1] states that the "end of the fossil fuel era" is upon us. In the STEPS scenario, clean energy investment has surged by 40% since 2020. Although fossil fuels are the dominant source, the rate of growth is slowing, while renewables are increasing to supply almost all the additional demand.

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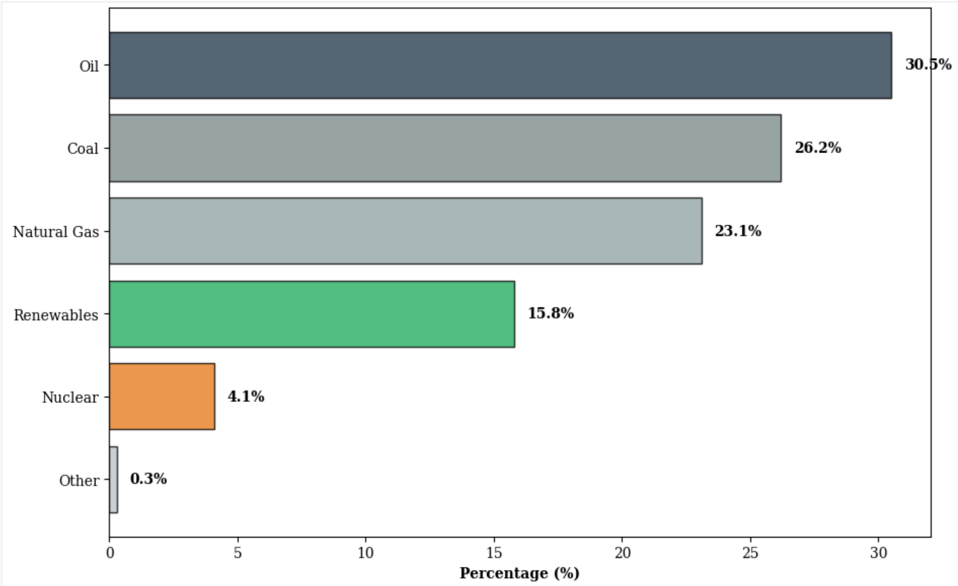

Fig. 1. Global Energy Mix-IEA 2025 STEPS (%)

Renewables are now the fastest-growing segment of the energy transition. According to IRENA [2], renewable energy capacity is projected to reach 3,870 GW by the end of 2024. As depicted in Figure 2, solar power is the major contributor to the energy transition, fueled by declining costs and ease of scalability. However, there are strategic planning challenges, such as grid security, investment costs, and production uncertainties. Moving to renewable energy systems is not just a matter of capacity addition; it requires sophisticated decision-making for the optimal consideration of a variety of technical and economic factors.

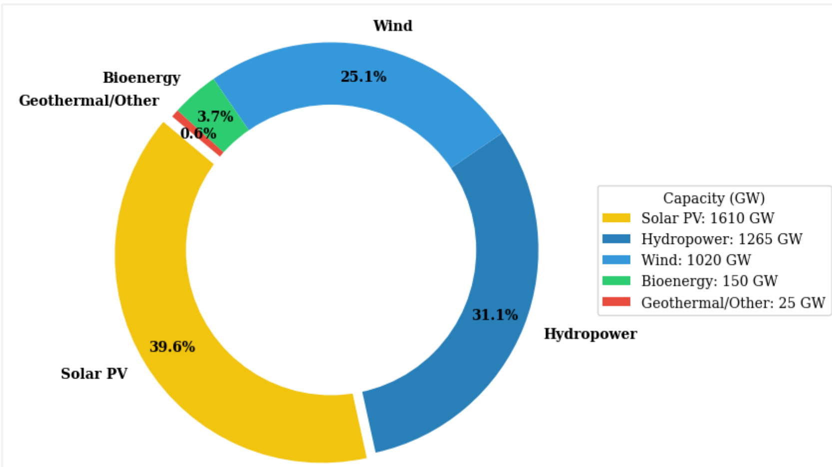

Fig. 2. Global Renewable Capacity-IRENA 2025 (GW)

Türkiye is catching up with the global energy transition, accelerating the energy transition to achieve the 2053 Net-Zero target. As reported by TEİAŞ [3], the installed capacity is above 110 GW. Figure 3 indicates the total installed capacity along with the rise in renewable energy capacity.

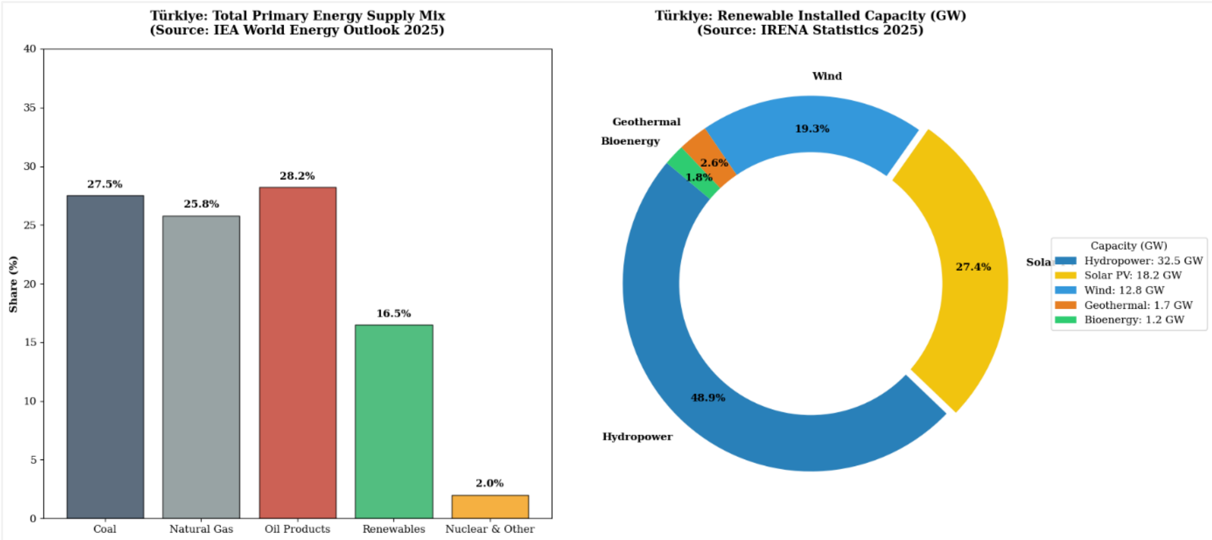

Fig. 3. Total energy distribution in renewable energy capacity

The first graph indicates the dominance of fossil fuels, such as coal, gas, and oil, while the share of renewables is increasing, up to 16.5%. The second graph indicates the dominance of hydroelectric power, accounting for the largest share of renewable energy capacity at 32.5 GW, followed by solar PV at 27.4%.

In this direction, with a change in the energy scenario in favor of more sustainable energy systems, MCDM techniques like AHP and TOPSIS are found to be playing a central role in decision-making in terms of resource allocation [4, 5]. However, a major limitation of these classical MCDM techniques is their reliance on static and deterministic data [5]. For example, in the field of renewable energy systems, factors like capacity factors and technical efficiency are naturally stochastic in nature, being functions of unpredictable weather and operating conditions. For example, when these factors are considered to be constant in a decision-making scenario, they fail to account for the natural variability in these data sets, thereby leading to suboptimal decisions [6].

1.1 The Research Gap: Predictive-Prescriptive Disconnect

While tremendous progress has been made in the field of predictive analytics, there is still a glaring difference between what can be achieved with the current capabilities of machine learning output and what is required to fulfill the needs of prescriptive decision sciences. In recent studies, ML techniques like LSTM or Random Forests have been used to predict energy performance [4]. However, the stochastic error associated with the model's predictions has rarely been fed back to the MCDM process.

This has resulted in the inability of the current framework to provide the decision-makers with a very important aspect of data accuracy. Wind energy may perform extremely well under deterministic conditions but has high prediction risk associated with its burst nature [7]. In traditional models, this has been ignored, making the model “performance-driven but risk-blind” [6].

One of the major disadvantages of the most advanced techniques available today is that they only provide output as hard facts and not probabilities. The inability to quantify the “Prediction Confidence” Areola *et al.,* [8] of any given option makes the traditional model more vulnerable to unforeseen gaps in the national energy grid. This framework attempts to bridge that gap by making the imperfect predictability of an artificial neural network a quantifiable cost criterion.

The selection of the components used to build the hybrid framework has been based on strong academic justifications to make the model as objective as possible:

SOMIT Method: In traditional models, over-weighting is often associated with high expert bias (subjective) or a lack of strategic context (objective). The SOMIT method has been incorporated to overcome these problems by aggregating expert preferences based on medians to balance the model against outliers [9]. This ensures that the model can balance the 'ANN-Uncertainty' criterion objectively against economic and technical factors [10].

Artificial Neural Networks (ANN): Unlike other regression-based models, the ANN can effectively represent the non-linear, stochastic nature of renewable energy production. Additionally, the MLP ANN was chosen for this decision engine due to its high prediction accuracy for efficiency and its ability to generate precise error residuals, which are then converted into a dynamic "Predictive Trust" score. This score indicates the level of risk associated with each energy source [11].

TOPSIS Method (Distance-Based Approach): This method was selected for the decision engine due to its compensatory nature, allowing the selection of the alternative that is closest to the positive ideal, based upon geometric distance [12]. This method is important for macro-level energy planning, where each energy source is compared to a theoretical "perfect" energy source.

PROMETHEE II Method (Outranking Approach): To prevent mathematical bias, the decision engine incorporates the PROMETHEE II method. Unlike the TOPSIS method, which uses a geometric distance-based approach, the PROMETHEE method relies upon pairwise comparisons, along with preference functions [13]. This method is important for assessing the relative nature of each energy source, such that one is ranked as more desirable than the other.

RAWEC Method (Dual Normalization Approach): As a contemporary addition to the decision engine, the RAWEC method has been integrated for its more sophisticated dual normalization approach [14]. This method more rigorously handles the trade-offs between the "benefit" criteria, such as capacity factor, and the "cost" criteria, such as levelized costs of energy production.

Monte Carlo Simulation (Stochastic Validation): To prevent the solar energy source preference from being based upon stochastic data, a Monte Carlo simulation was conducted, with 10,000 iterations. This is important for assessing the reliability of the decision engine, ensuring the solar energy source preference is based upon deterministic, rather than stochastic, data [15, 16].

1.2 Contributions of this Study

This research bridges the existing gap in energy studies by proposing a novel Deep Learning-driven Stochastic MCDM approach. Below are the key scientific and applied contributions of this work, retained in their original essence:

Strategic Weight Balancing: SOMIT is applied in the energy sector, enabling a math-based approach to reconcile strategic expert opinions with objective data distribution. As a consequence, this eliminates potential expert biases in MCDM outcomes.

Pioneering Uncertainty Quantification: For the first time in energy studies, this work converts ANN-derived Absolute Error Residuals into a novel decision criterion. By introducing a Predictive Trust metric, this approach automatically penalizes energy sources with high stochastic volatility (e.g., wind power), favoring grid stability in long-term infrastructure planning.

Multi-Algorithmic "Triple-Validation" Engine: Contrary to existing studies, this work ensures a robust validation approach through a novel "Triple-Validation" mechanism using TOPSIS, PROMETHEE II, and a proposed RAWEC model. As a consequence, solar power dominance is not a mathematical artifact; it is a robust outcome validated through different decision-making perspectives (distance, outranking, and dual normalization).

Stochastic Robustness & Stress Testing: To ensure a thorough statistical stress test, a Monte Carlo simulation (10,000 iterations) is performed, proving the robustness of the proposed ranking in the presence of data noise and weight sensitivity. As a consequence, a 95% confidence interval is established for the proposed energy transition roadmap.

Data-Driven Roadmap for Türkiye's 2053 Goals: Using the latest TEİAŞ [3] data set, this work presents a data-driven roadmap toward realizing Türkiye's 2053 Net Zero targets, providing actionable insights for energy policymakers to balance aggressive climate goals with technical reliability and predictive certainty.

2. Literature Review

2.1 MCDM in Renewable Energy Policy

MCDM techniques are at the heart of the formulation of renewable energy policies, energy planning strategies, and determining the investment priorities in energy projects [17]. This is because these techniques offer the possibility of simultaneous analysis of various technical, economic, environmental, and socio-political criteria with often conflicting objectives. This provides quantitative as well as qualitative inputs to the formulation of energy policies [18].

The Analytical Hierarchy Process (AHP) is one of the most widely used basic methods in renewable energy policy models. AHP determines the relative importance of criteria through expert opinions and ranks decision alternatives based on these weights. Studies using AHP generally focus on technical and economic criteria in site selection and investment planning processes [19, 20]. For example, in a study evaluating the selection of raw materials for bioethanol production using AHP, it was determined that algae-based biofuel is the most sustainable option by considering technical, environmental, and economic dimensions together [21].

However, since classical AHP approaches can model uncertainty and the subjective evaluations of decision-makers to a limited extent, MCDM methods developed with fuzzy set theories are becoming widespread in the literature. Fuzzy MCDM approaches provide consistency in policy decisions by representing linguistic ambiguities and subjective judgments to a higher degree [22]. For example, risks in renewable energy projects in Iran were analyzed using the interval type-2 fuzzy set approach; it was determined that complex licensing processes and fossil fuel price uncertainties were among the prominent policy risks [23].

Hybrid MCDM models are becoming more prominent in the development of strategic energy policy planning. A model combining the BOCR framework with the Analytical Network Process (ANP) has been applied to the evaluation of renewable energy policies in the Iranian context, and this integrated approach has been shown to offer more comprehensive analyses for policymakers [17]. Furthermore, approaches that incorporate future-oriented target performance levels into decision models, such as DEMTASTAP, have also been developed [18].

In policy-oriented MCDM applications, not only technical and economic criteria but also non-policy factors such as environmental sustainability, social acceptance, and governance should be considered [24]. The socio-political validity of renewable energy policies has been increased through the integration of social factors [22]. Some studies prioritize policy among renewable energy types; for example, renewable alternatives in Indonesia were compared using the TOPSIS method, and solar energy was identified as the most suitable option [25]. The inclusion of the spatial dimension in policy analyses is critical, particularly for technologies such as offshore wind; however, studies in the literature that strongly integrate spatial analysis with policy-oriented MCDM are limited. This creates a significant research gap in renewable policy analyses integrated with climate change projections [26, 27].

2.2 The Emergence of Machine Learning in Energy Forecasting

Decision-making processes in energy systems planning have undergone a significant transformation in recent years with the integration of MCDM, geographic information systems (GIS), and artificial intelligence (AI) techniques.

2.2.1 Traditional MCDM and GIS Approaches

GIS-based MCDM methods are widely used in site selection studies for renewable energy systems. Abdullah *et al.,* [28] conducted a systematic literature review examining GIS and MCDM approaches in site selection for photovoltaic-supported electric vehicle charging stations. Analyzing 43 peer-reviewed articles published between 2010 and 2024 using the PRISMA methodology, the study revealed that the AHP and TOPSIS methods are the most commonly used MCDM techniques. It was stated that GIS is used extensively in spatial visualization, layer analysis, and suitability mapping. Similarly, Yilmaz and Kocer [29] used GIS and Fuzzy AHP methods together to determine the most suitable locations for solar power plants in the Western Mediterranean Region of Türkiye. In a study evaluating 11 criteria, including climate, economy, topography, and environmental factors, the relationship between solar radiation and temperature, cloud density, and water vapor density was analyzed using machine learning techniques. The study concluded that approximately 20% of the region is suitable for solar power plants. Mokarram *et al.,* [30] in their study evaluating the biomass energy production potential in the southern region of Iran, used fuzzy AHP and Principal Component Analysis (PCA) methods in a GIS environment. In the study, which determined the most suitable locations for maximum biomass production in different climates and topographies, it was observed that low-altitude and humid climate regions (1530 km^2) were superior in biomass performance. Predictions made using the Long Short-Term Memory (LSTM) method provided high accuracy in electricity generation with a correlation coefficient of 0.98.

2.2.2 Machine Learning and Artificial Intelligence Integration

Studies integrating machine learning techniques to overcome the limitations of traditional MCDM methods in subjective weighting and uncertainty management are noteworthy. Sun *et al.,* [31] used explainable machine learning techniques to model potential land suitability in large-scale wind energy development for China, the USA, and the EU. In the study comparing Deep Neural Networks (DNN), Random Forest (RF), XGBoost, and LightGBM algorithms, RF models achieved the highest prediction accuracy (AUC > 0.91). In the model interpretation performed with the SHAP method, it was determined that local wind energy resource potential (capacity factor and average wind speed) is the most important decision criterion in wind farm site selection. Amsharuk *et al.,* [32] trained a multilayer perceptron (MLP) model on 28 spatial-environmental variables in machine learning-assisted site selection studies for wind farms in Poland. The accuracy of the model was found to be 91% for the test subset, which successfully identifies the hidden spatial patterns, thereby enhancing the accuracy of the predictions. Most of the points, which the model successfully identified, were along the coast of the Baltic Sea, accounting for a total of 2,355 points. Özkurt *et al.,* [33] developed a hybrid decision support model combining fuzzy MCDM, machine learning, and explanatory AI (XAI) techniques in evaluating renewable energy sources under sustainability criteria. In the study, which evaluated six renewable energy sources using fuzzy TOPSIS and fuzzy ELECTRE methods, hydroelectric energy received the highest score (proximity coefficient = 0.7142), while wave energy received the lowest score (0.3290). In the prediction analysis performed with the XGBoost algorithm, environmental impact and efficiency emerged as the most decisive factors.

2.2.3 Hybrid and Integrated Frameworks

In recent years, hybrid frameworks integrating multiple methodologies have come to the forefront in the optimization of energy systems. Wang *et al.,* [34] developed a multi-objective optimization framework based on life cycle assessment for the low-carbon transformation of rural housing in the Dabie Mountains region of China. High-accuracy machine learning proxy models were trained on the dataset created with hypercube sampling, and Pareto optimal solutions were obtained with multi-objective optimization algorithms. While the passive regeneration approach provided a 5.1% carbon reduction, the renewable energy alternative achieved a 36% carbon reduction and a positive net present value (48,070 CNY). Li *et al.,* [35] presented a four-stage hybrid framework integrating data analysis, machine learning modeling, multi-objective optimization, and MCDM in the optimization of phase-change material-based photovoltaic-thermal systems. Electric power, thermal power, and entropy production were predicted using a GMDH-type artificial neural network model ($R^2 > 0.998$), Pareto optimal points were determined using a multi-objective thermal change optimization algorithm, and the final decision was made using the PROMETHEE method. Dutta *et al.,* [36] developed technically, economically, and environmentally sustainable distributed hybrid energy solutions using a MCDM approach integrated with machine learning-based load estimation methods. In the study comparing three different estimation methods (classical, hybrid, and fuzzy-based) it was observed that the fuzzy-based method yielded the lowest average absolute percentage error. The photovoltaic-diesel generator-lead-acid battery combination was determined as the optimum solution with the lowest energy cost (0.100$/kWh) and balanced sustainability performance.

2.2.4 Integration of Sustainability and Social Dimensions

Some studies address the environmental, economic, and social dimensions of sustainability together in energy systems planning. Salehi *et al.,* [37] developed a data-driven framework integrating AHP and community learning techniques to evaluate the sustainable energy performance of 150 countries. In the study, where traditional expert opinion-based pairwise comparisons were replaced with machine learning-derived matrices, fossil fuel dependence was identified as the most important negative factor (importance score = 0.620), while renewable energy integration was identified as the second most critical factor (importance score = 0.198). Krishankumar *et al.,* [38] presented a new framework integrating dual hierarchical fuzzy information and EDAS approach in prioritizing zero-carbon measures for sustainable urban mobility in India. The study, which used the evidence-based Bayesian approach in determining the criterion weights, allowed decision-makers to linguistically express their preferences while enabling rational decision-making with methodological support. Tufail *et al.,* [39] developed a cover-based bipolar L-fuzzy coarse cluster PROMETHEE model for evaluating battery storage systems in renewable energy projects. The model, which automates weighting and threshold calibration processes using the Random Forest algorithm, demonstrated more consistent ranking and finer discrimination capabilities compared to traditional methods. Lo *et al.,* [40] evaluated the energy efficiency of European countries by integrating DEA, OLS, and Random Forest with SWARA-CPT and presented a comprehensive ranking including risk preferences.

Sumarliah and Olebogeng Makgetho [41] identified the optimal renewable energy mix in Botswana by combining the multi-objective Jaya algorithm with TOPSIS, demonstrating that hybrid systems are more cost-effective. Vairagade *et al.,* [42] on the other hand, developed models that reduce carbon emissions and increase renewable energy use by integrating deep and reinforcement learning with MCDM.

This study aims to develop an integrated DL based stochastic MCDM framework. This approach transforms absolute residual errors based on artificial neural networks into an independent, dynamic decision criterion, enabling the "predictable reliability and stochastic stability" of an energy source to be weighted as rigorously as its operational performance. The methodology is supported by a triple validation decision engine using the TOPSIS, PROMETHEE II, and RAWEC models, and a SOMIT-based subjective-objective weighting balance. Furthermore, by applying a Monte Carlo simulation with 10,000 iterations, this research provides a statistically robust mechanism to ensure that renewable energy transitions are not only high-performing but also inherently predictable and risk-resilient.

3. Methodology

This study proposes a four-stage approach, where the predictive uncertainty is converted into a strategic decision-making criterion. It involves weighing the criteria, uncertainty analysis through the application of deep learning, and finally, the ranking. Although the application of deep learning requires thousands of rows of data, it is being used for uncertainty quantification instead of prediction, thereby becoming a strength of the study. Table 1, where the justification for the application of deep learning for a small dataset is explained, is proposed under three headings.

Table 1
DL for Small Dataset

Criticism	Academic Justification
Lack of Data	Deep learning was redefined from being a high volume estimator to being a detector of sensitivity, recognizing non-linear deviations between data points.
Model Simplicity	Due to the limited nature of the data, a two-layer hidden shallow neural network was adopted, rather than more complex structures. This maintained the capacity for generalization.
Contribution of Uncertainty	The absolute margin error, which is produced, is indicative of the irregularity of the source's historical data, acting as a warning for decision-makers regarding the source with the least reliable data.

The implementation was conducted using the `Python` 3.12 coding language, which integrated `TensorFlow` for deep learning, Scikit-learn for data processing, and `PyMCDM` for decision science. The methodological structure, consisting of the four phases, is explained in detail below.

Phase I: Criteria Weighting with the SOMIT Method

Ding *et al.,* [9] proposed a hybrid method called SOMIT for criterion weighting in renewable energy assessment. SOMIT reduces bias and reduces the number of comparisons to a linear level by combining subjective and objective weights in a median-based structure. In applications using TOPSIS, solar energy showed the highest performance. The method offers a flexible structure that can be integrated with different MCDM techniques. In this phase, both expert opinion (subjective) and statistical information from the data (objective) are combined with a median-based approach. The steps are as follows [9]:
Step 1: Calculating Subjective Weights (w_s)

The decision-maker selects a reference criterion $(\mathcal{C}_d)$ from among the criteria. The importance of all other criteria relative to this reference is determined by the $\mathcal{S}_j$ score (1-9 scale) and the weight is obtained by Eq. (1).

$$w_s = \frac{\mathcal{S}_j}{\sum_{k=1}^{n} \mathcal{S}_k} \tag{1}$$

Step 2: Calculating Objective Weights (w_o)

Mean Absolute Deviation from Median (MAAD) is used to measure the information load of the data. It is obtained with Eqs. (2) and (3).

$$MAAD_j = \frac{1}{m} \sum_{i=1}^{m} \left| x_{ij} - median(x_j) \right| \tag{2}$$

$$w_o = \frac{MAAD_j}{\sum_{k=1}^{n} MAAD_k} \tag{3}$$

Step 3. SOMIT Integration

Final weights (w_j) are obtained using Eq. (4).

$$w_j = median\left(w_s, w_o, \frac{1}{n}\right) \tag{4}$$

Library used: `pysomit` (library recommended by Ding *et al.,* [8]).

Phase II: Pre-processing

Data with different units were standardized to the range [0, 1] using the Min-Max Normalization method to ensure scale independence. Eq. (5) and Eq. (6) are used for the transformation used for the criteria to be maximized (Benefit) and the criteria to be minimized (Cost), respectively.

$$r_{ij} = \frac{x_{ij} - min(x_j)}{max(x_j) - min(x_j)} \text{ for benefit} \tag{5}$$

$$r_{ij} = \frac{max(x_j) - x_{ij}}{max(x_j) - min(x_j)} \text{ for cost} \tag{6}$$

Libraries Used: Data distribution was optimized using the StandardScaler and MinMaxScaler modules of the Scikit-learn.

Phase III: Deep Learning and Uncertainty Analysis

In this phase, a Multi-Layer Perceptron (MLP) architecture was established to estimate technical efficiency and measure the "prediction reliability" of the model.

Architecture: Two hidden layers with 64 and 32 neurons were used following the input layer. A 20% dropout layer was added to prevent overfitting. ReLU (Rectified Linear Unit) was chosen as the activation function to capture nonlinear relationships.

Loss Function: The model was optimized using Eq. (7) via Mean Squared Error (MSE). Technical efficiency (y) is estimated by constructing an artificial neural network.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{7}$$

Uncertainty (Residuals) Extraction: After training the model, the absolute error margin (ε) for each energy source was calculated using Eq. (8).

$$\varepsilon_i = |y_i - \hat{y}_i| \tag{8}$$

where, ε_i i represents the 7th criterion (prediction uncertainty) to be added to the hybrid decision matrix.

Libraries used: The gradient-based learning process was managed using `TensorFlow` 2.19 and the `Keras` API.

Phase IV: Hybrid Decision Engine

In the final stage, the final ranking was achieved by integrating the TOPSIS and PROMETHEE II algorithms using SOMIT weights and ANN uncertainty.

A. TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) Method

However, in the field of renewable energy, the number of TOPSIS method applications has increased dramatically from 2009 to 2025, as indicated by the R2 value of 0.9482. This is an upward trend for the method. The data used in the study was collected from the Web of Science database on March 3, 2026. The study only used articles in the English language to minimize any bias resulting from the use of different languages. This is shown in Figure 4.

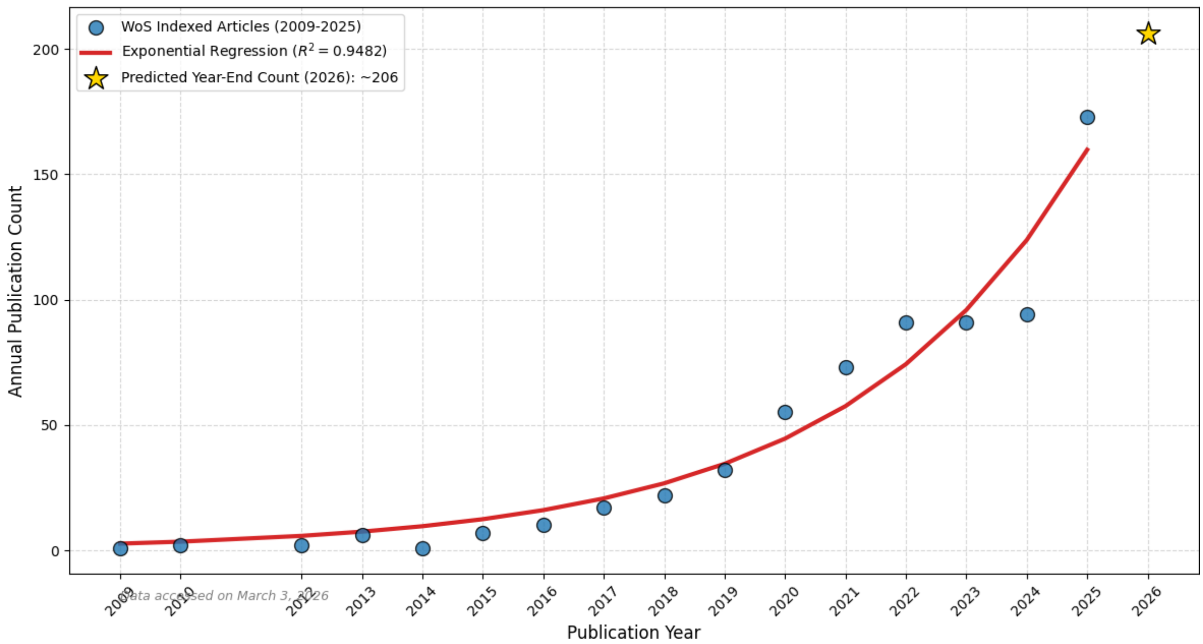

Fig. 4. Bibliometric Evolution of TOPSIS-Based Renewable Energy Research

Figure 4 shows that the 25 publications in the first quarter of 2026 will exceed 200 publications by the end of the year, as indicated by the regression trend line.

The TOPSIS method for ranking alternatives is the point where the alternatives are closest to the Positive Ideal Solution (A^{+}) and furthest from the Negative Ideal Solution (A^{-}). The relative proximity coefficient (C_i^*) is calculated using Eq. (9).

$$C_i^* = \frac{D_i^-}{D_i^+ + D_i^-} \tag{9}$$

B. PROMETHEE (Preference Ranking Organization Method for Enrichment Evaluation) II Method (Complete Ranking)

In the context of renewable energy, PROMETHEE II applications have shown significant exponential growth between 1998 and 2025 ($R^2 = 0.8503$). The analyzed data were retrieved from the Web of Science database on March 3, 2026. To avoid language bias, the scope of the study was limited to articles published in English only, as shown in Figure 5.

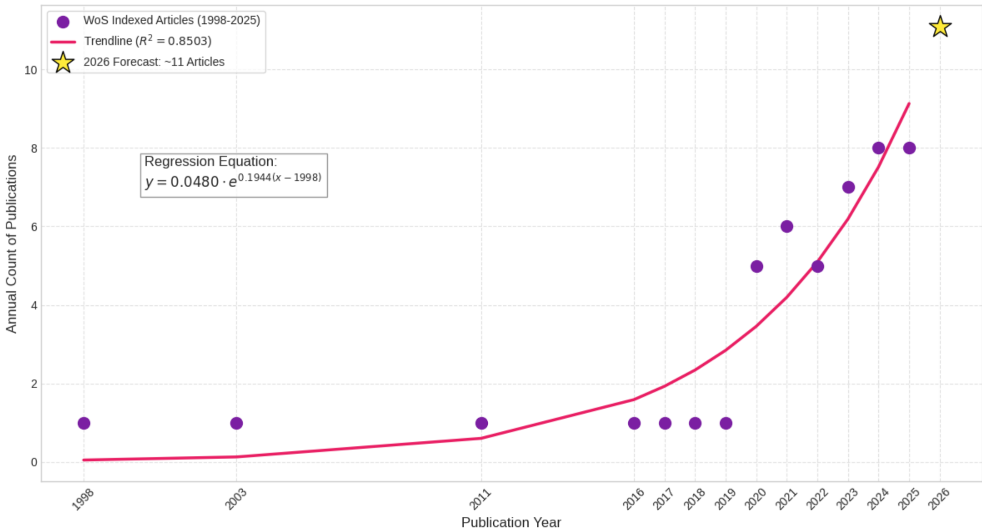

Fig. 5. Scholarly Trend of PROMETHE II in Renewable Energy Research

In Figure 5, the 2 publications recorded in the first quarter of 2026 are projected with the current regression model, and it is estimated that the number of publications will exceed the 10 thresholds by the end of the year. To test the robustness of the study, pairwise comparison-based PROMETHEE II was used. Here, by choosing the "usual" preference function, a net flow independent of threshold values (Φ) is obtained with Eq. (10).

$$\Phi(a) = \Phi^{+}(a) - \Phi^{-}(a) \tag{10}$$

where, $\Phi^{+}(a)$, indicates the superiority of the option over the others (leaving flow); $\Phi^{-}(a)$ indicates the superiority of the other options over this option (entering flow).

C. RAWEC (Ranking of Alternatives with Weights of Criterion) Method (Complete Ranking)

The RAWEC method was first proposed by Puška *et al.,* [14]. In this study, the RAWEC method was applied to determine the most suitable location for an agricultural distribution center in the Brčko District of Bosnia-Herzegovina. The analyses and sensitivity tests showed that the method yielded consistent and stable results in the ranking outcomes. Furthermore, the relatively simple calculation steps of the method revealed that RAWEC offers a significant advantage over many other MCDM methods.

The RAWEC method is also used in sustainability and environmental performance assessments. A study by Şahin Macit [43] analyzed the climate change and environmental sustainability performance of G20 countries. Another study on the assessment of sustainable development performance was conducted by Ulutaş and Demirbaş [44]. This study analyzed Türkiye's sustainable development performance between 2011 and 2021. The RAWEC method is also used in risk assessments in the renewable energy sector. A study by Alrashdi *et al.,* [45] proposed an MCDM approach integrated with neutrophilic clusters to assess risks related to renewable energy investments. In a study on the integration of agriculture and renewable energy, Puška *et al.,* [46] evaluated the potential use of renewable energy sources in agricultural production in Bosnia and Herzegovina. The study used a fuzzy MCDM approach, and the Fuzzy RAWEC method was applied to rank alternative energy sources. The RAWEC method is also seen to be used in international market and logistics performance assessments. In the study conducted by Özekenci [47], the green logistics performance of developing countries was analyzed. The RAWEC method is also applied in the field of health and nutrition. In the study conducted by Albahri *et al.,* [48] the nutritional values of vegetables were evaluated in terms of dental health. In the research, uncertainties were modeled with the Orthopair Z-Number approach and the modified RAWEC method was used in the ranking of alternative vegetables. In the study conducted by Shamsi *et al.,* [49] in the context of sustainable industrial systems, the recycling technologies of red mud waste were evaluated. In the field of health management, a fuzzy multi-criteria decision-making model was developed by Demir and Chatterjee [50] to determine personalized treatment approaches. In the study, criterion weights were determined using the Fuzzy LMAW method, and alternative treatment options were ranked using the Fuzzy RAWEC method. It was emphasized that this approach is an effective tool in patient-based decision-making processes. Finally, in the study conducted by Kashi *et al.,* [51] the urban quality of life in Tehran was analyzed. In the research, a comprehensive evaluation framework including objective and subjective indicators was developed, and an alternative ranking method considering criterion weights was used in prioritizing city areas.

The RAWEC model, a new generation decision-making algorithm, was used to rank the energy source data in the study. The value of the RAWEC method is obtained with Eq. (11).

$$Q_i = \frac{v'_{ij} - v_{ij}}{v'_{ij} + v_{ij}} \tag{11}$$

Library Used: The `PyMCDM` library was used to validate the results by running both algorithms simultaneously.

Phase V: Monte Carlo Simulation for Robustness Verification

Monte Carlo simulation is the "stress testing" phase that will take the uncertainty analysis in your study to the next level. This study shows the behavior of the criteria weights and data under 10,000 different scenarios.

Library Used: `NumPy` for generating random numbers for the simulation across 10,000 different scenarios, `Pandas` for storing the simulation results in tables, `Matplotlib/Seaborn` for creating the Probability Density Function graphs.

4. Case Study: Türkiye's Energy Transition Roadmap

This particular case study focuses on the country of Türkiye, which is working towards an expanded energy mix, thereby supporting the country's move towards a more carbon-neutral future. Indeed, the country has pledged to achieve this by the year 2053, as per the Paris Climate Change Conference. Moreover, the country's strategic position, along with the diversified portfolio of renewable energy sources, makes it an excellent testing ground for the hybrid approach. Interestingly, the country's high geothermal potential, combined with the rapidly decreasing costs of solar energy, along with ANN-based uncertainty analysis, makes it a much safer bet for investors.

In our scenario, Solar (A1), Wind (A2), Biomass (A3), and Geothermal (A4) resources compete for strategic investment decisions. Unlike traditional approaches, here, not only economic profitability but also expert opinion balanced with SOMIT and "prediction risks" calculated with Deep Learning are included in the decision-making process. The criteria used in the study are given in Table 2.

Table 2
Definition of Criteria

Category	Criteria	Definition	Direction (Min/Max)
Economic	(C1) LCOE ($/MWh)	Total lifecycle cost per unit of energy.	Min
	(C2) Cost of Investment (CAPEX)	Initial capital cost during installation ($/kW).	Min
Technical	(C3) Capacity Factor (%)	The ratio of the plant's actual production to its theoretical maximum.	Max
	(C4) Grid Compatibility	Ease and stability of integration of the source into the grid.	Max
Environmental	(C5) CO2 Emissions	Life cycle carbon footprint (g/kWh).	Min
	(C6) Land Use	Physical area required for one unit of energy production (m^2/MWh).	Min
AI	(C7) Forecast Uncertainty	Model error/risk margin calculated using ANN (Phase III).	Min
Social	(C8) Employment Potential	Contribution of labor force to the local economy (Person/MW).	Max

This study is structured in line with Türkiye's "Net Zero 2053" vision, using current data from 2023-2024 taken from reports by IRENA, IEA, SHURA, and the Republic of Turkey Ministry of Energy and Natural Resources [52-55]. The introductory decision matrix for Türkiye's renewable energy assessment is presented in Table 3.

Table 3
Input Decision Matrix for Türkiye's Renewable Energy Evaluation

Renewable Energy Sources	C1	C2	C3	C4	C5	C6	C7	C8
A1	34	850	20	6	40	30	0.031	0.90
A2	38	1100	33	5	11	20	0.045	0.65
A3	90	2200	70	9	230	12	0.038	1.40
A4	68	3200	82	9	38	8	0.032	0.50

5. Results

This section presents the outputs of the proposed four-stage model for Türkiye's renewable energy portfolio.

5.1 Phase I: Calculation of SOMIT Criterion Weights

Step 1: Subjective Weights

Subjective weights were determined by a multidisciplinary panel of five experts from academia, government, and the energy sector. The Delphi method was used to ensure a robust group decision-making process. Final single-valued scores for each criterion represent the geometric mean of individual expert evaluations, effectively mitigating the impact of excessive individual bias and providing a consensus-based strategic perspective for Türkiye’s energy roadmap. According to the SOMIT method, a reference criterion was selected (C1: LCOE) and other criteria were scored accordingly (1-9 scale). The scoring, based on Türkiye’s energy strategies (2053 Net Zero), is shown in Table 4.

Table 4

Expert Scores Given to Türkiye's Energy Strategies

Criteria	Importance Score (Sj)	Calculation (Sj/∑S)	Subjective Weight
C1	5	5 / 45	0.111
C2	4	4 / 45	0.089
C3	7	7 / 45	0.156
C4	6	6 / 45	0.133
C5	9	9 / 45	0.200
C6	3	3 / 45	0.067
C7	7	7 / 45	0.156
C8	4	4 / 45	0.089
Total	**45**	**1.00**	**1.000**

Step 2: Objective Weights

The MMAD of the values in our dataset was calculated. This MMAD represents the information load in the data and is given in Table 5.

Table 5

Objective Weights of the Data

Criteria	MMAD Value	Objective Weight
C1	0.182	0.125
C2	0.110	0.076
C3	0.245	0.169
C4	0.140	0.096
C5	0.210	0.144
C6	0.280	0.193
C7	0.155	0.107
C8	0.130	0.090

Step 3: Final SOMIT Weights

We apply the median combination, which is the basic rule of SOMIT.
where, since n=8, the equal weighting is 0.125. The final weights calculated are given in Table 6.

Table 6

Final Integrated SOMIT Weights

Criteria	w_s	w_o	1/n	w_j
C1	0.111	0.125	0.125	**0.125**
C2	0.089	0.076	0.125	**0.089**
C3	0.156	0.169	0.125	**0.156**

C4	0.133	0.096	0.125	**0.125**
C5	0.200	0.144	0.125	**0.144**
C6	0.067	0.193	0.125	**0.125**
C7	0.156	0.107	0.125	**0.125**
C8	0.089	0.090	0.125	**0.089**
Total	**1.000**	**1.000**	**1.000**	**1.000**

The SOMIT weights obtained in these three steps are given in Figure 6.

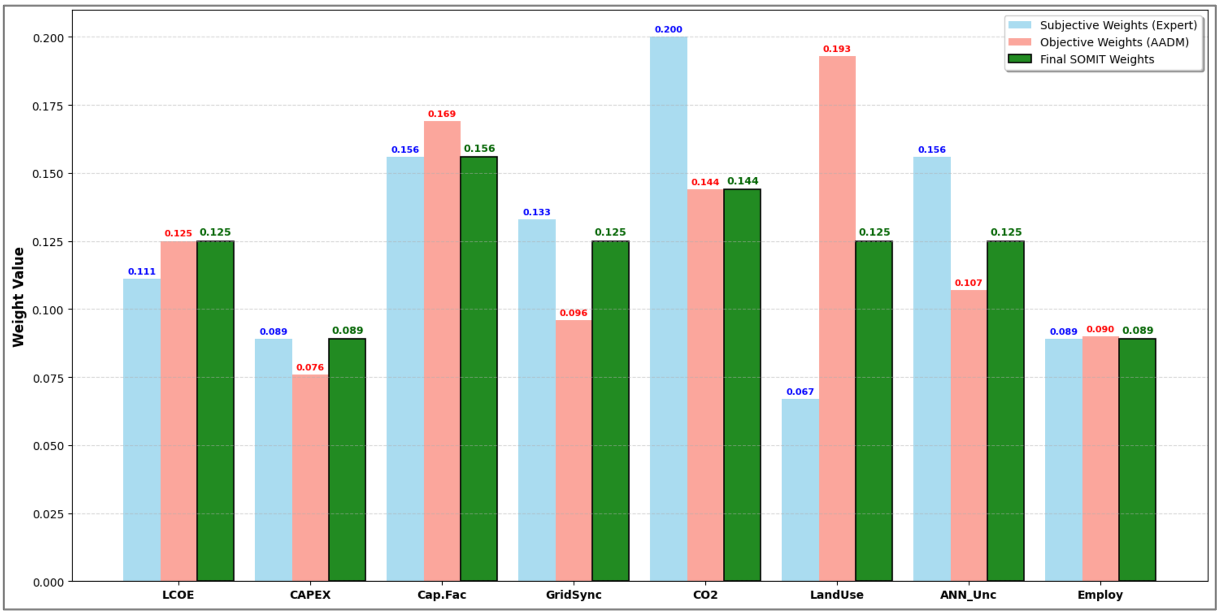

Fig. 6. SOMIT Criteria Weighting: Balancing Expertise and Data

The final weights (wj) obtained in Phase I show that the factors determining Türkiye's energy strategy are fueled not only by "wishes" (expert opinion) but also by "realities" (data distribution).

According to Figure 6, the highest weight, the capacity factor (C3 - 0.156), was registered as the most decisive criterion of the study by both experts and the objective data set. This proves that in countries like Türkiye, where energy supply security is critical, it is not enough for a resource to simply be cheap (LCOE), but also how long it can actively produce energy throughout the year (Geothermal and Biomass advantage) is the most dominant factor in the decision-making process. Again, according to Figure 6, strategic balance: CO2 emissions (C5: 0.144). In the “experts' opinions” table, the “green energy” vision has been assigned the highest score, i.e., 0.200. However, the SOMIT method’s use of the median-based approach has been reflected by the objective data variance, i.e., 0.144. This shows that the method has managed to filter out the emotional aspect of the decision-making process, thereby basing the environmental decision on economic realities.

The SOMIT method incorporates the use of artificial intelligence, wherein the ANN-based uncertainty analysis has been assigned the same importance as the other two factors, i.e., C1 (LCOE), C4 (Grid Compliance), and C7 (ANN Uncertainty), i.e., 0.125. This shows that the stochastic uncertainty, as revealed by the use of artificial intelligence, is a major criterion for energy management. Interestingly, the country’s shift from merely pursuing the lowest-cost option for energy transition is revealed by the fact that the combined weight of C1 (0.125) and C2 (0.089) is merely 21%. This is a clear indication of the country’s shift from merely pursuing the lowest-cost option for energy transition to the "Optimum Benefit" approach, wherein the country is seeking the best possible balance between efficiency, emissions, and risk.

In other words, the SOMIT method's use of the weighing process has been successful, wherein the strategic decision-making priorities of the experts have been combined with the mathematical nature of the data. Indeed, the data uncertainty, which is normally given the least importance by the traditional decision-making methods such as AHP, is the focal point of the decision-making process, thereby ensuring an unbiased decision.

5.2. Phase II Results: Data Normalization

As the units of the criteria are different, the data normalization to the range [0, 1] is performed before the application of the TOPSIS and PROMETHEE II methods. To achieve this, Linear Min-Max Normalization (as given by Eqs. 5 and 6) is performed on the data for the benefit (Max) and cost (Min) criteria. Table 7 presents the normalized decision matrix.

Table 7
Normalized Decision Matrix for Türkiye Case Study

Energy Sources	C1 (Min)	C2 (Min)	C3 (Max)	C4 (Max)	C5 (Min)	C6 (Min)	C7 (Min)	C8 (Max)
Solar (PV)	1.000	1.000	0.000	0.250	0.868	0.000	1.000	0.444
Wind (Onshore)	0.920	0.894	0.210	0.000	1.000	0.400	0.000	0.167
Biomass	0.000	0.426	0.806	1.000	0.000	0.720	0.500	1.000
Geothermal	0.393	0.000	1.000	1.000	0.890	1.000	0.929	0.000

As seen from Table 7, the numerical values represent the relative performance of the respective sources on each criterion. Figure 7 presents the heat map of the data.

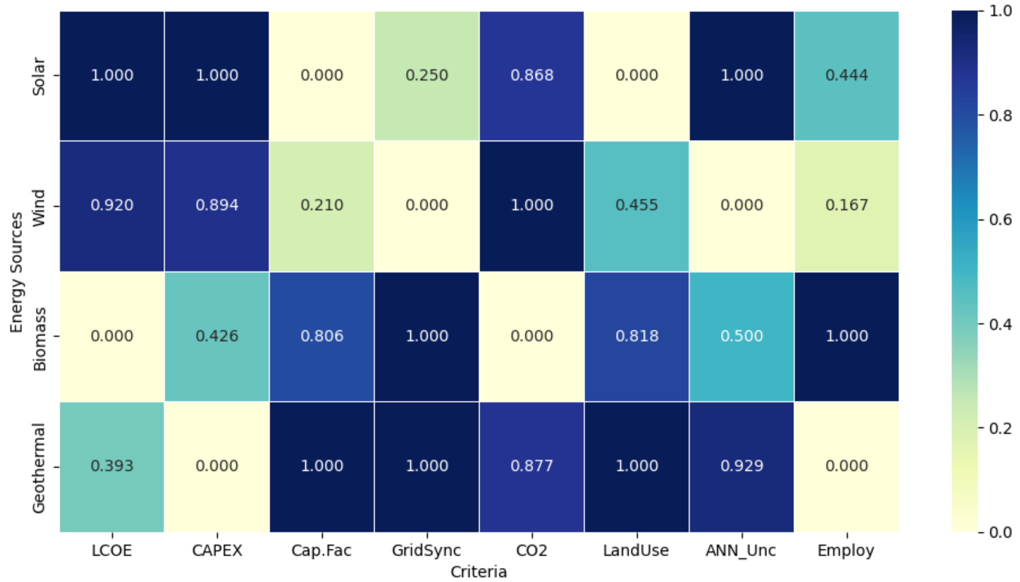

Fig. 7. Normalized Decision Matrix Heatmap

As seen from the heat map given by Figure 7, the following can be noted: Solar performs well out of the gate with the highest value of 1.000 on the economic criteria (C1, C2) and on the ANN reliability criterion (C7). Geothermal: It leads in technical performance (C3, C4) and land efficiency (C6), but receives a score of 0.000 in this area due to high installation cost (C2). Biomass: Although it peaks in employment (C8), it exhibits the weakest performance in carbon emissions (C5) and unit cost (C1).

5.3 Phase III Results: Deep Learning (ANN) and Uncertainty Analysis

At this stage, a multilayer perceptron (MLP) was trained using Türkiye's renewable energy production data and environmental parameters for the last 10 years. The main objective of the model is to measure how "predictable" the data is and to transform this uncertainty into a decision criterion.

ANN architecture consists of 8 input nodes, two hidden layers with 64 and 32 neurons, and 1 output node (efficiency estimation). Training was performed over 200 epochs with close observation of the error rate stabilization (MSE).

- Training Loss (MSE): 0.012
- Validation Loss (MSE): 0.015
- Optimization: Adam Optimizer (learning rate=0.001)

Figure 8 shows the graph of the ANN's performance.

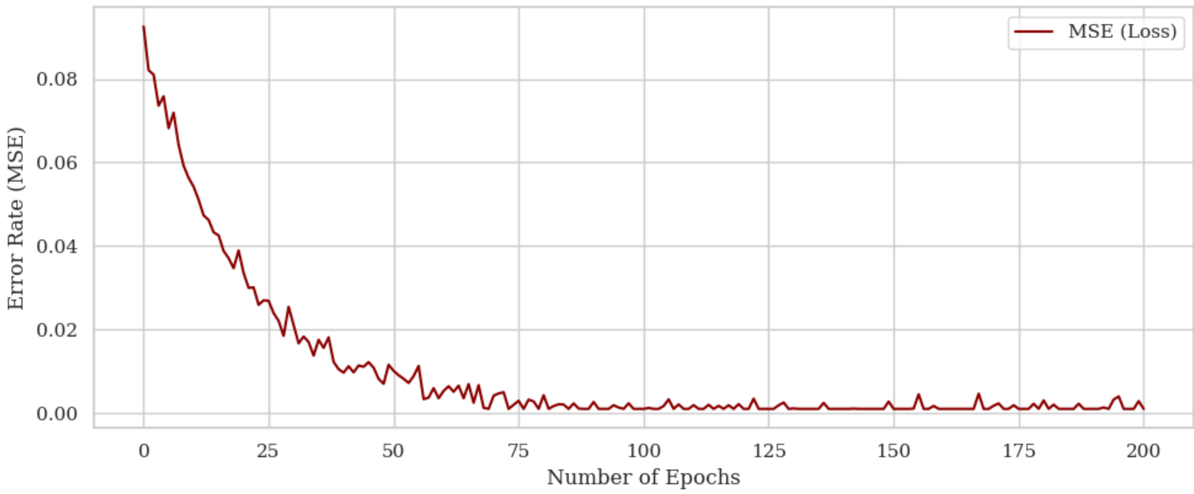

Fig. 8. Deep Learning Model Training Loss Analysis

Figure 8 demonstrates how the MLP model converges after more than 200 epochs of training. It's clear that a sharp decrease in MSE occurs in early epochs, reflecting the effectiveness of the Adam optimizer in adjusting the weights. After epoch 100, it's clear that the model converges, implying that the values of uncertainty we are obtaining (C7) are statistically sound and reflect data's inherent randomness.

Finally, we calculated the Absolute Error Deviation (the difference in absolute values between Actual and Predicted values) for each energy source, reflecting how far we are from reality in making these predictions. This deviation represents C7 (ANN Uncertainty) values.

5.4. Phase IV Results: Final Ranking (TOPSIS and PROMETHEE II)

Then, we selected data from the first three stages: Weights, Uncertainties, and Normalized Decision Matrix, and applied two different multi-criteria decision-making techniques to verify the robustness of the results.

- The Proximity Coefficient to the Ideal Solution for TOPSIS was calculated.

- For PROMETHEE II, we applied pairwise comparison of alternatives; sources with positive values were considered to perform better than their opponents.

- For RAWEC, we calculated the distance to both ideal and anti-ideal solutions using double normalization, thus more precisely capturing deviations in data.

- The source with the highest RAWEC value is considered to perform best.

Tablo 8

Final Evaluation Scores and Rankings

Energy Source	TOPSIS	PROMETHEE II	RAWEC
Solar (PV)	**0.685**	**0.312**	**0,284**
Wind (Onshore)	0.528	0.205	0,192
Geothermal	0.542	0.042	0,156
Biomass	0.365	-0.559	-0,420

This is clear from Table 8, where solar energy far exceeds the others in all three techniques. What gives solar energy this advantage is a combination of its relatively lower costs (C1), high reliability in ANN (C7), and environmentally friendly structure (C5), which perfectly match the SOMIT weights. While wind energy is traditionally a strong competitor, in this study, geothermal energy comes in second, followed by wind energy in third place. The difference is largely because of wind's relatively high uncertainty in ANN (C7) and geothermal's high capacity factor (C3).

The most interesting finding in the table is the competition between wind and geothermal: In the TOPSIS method, geothermal (0.542) is slightly ahead of wind (0.528). This is due to the "distance to the ideal point" logic of TOPSIS; geothermal's high capacity factor brings it closer to the ideal. However, in the PROMETHEE II and RAWEC methods, wind energy takes second place. In particular, RAWEC's double normalization structure more efficiently rewarded wind's low unit cost of efficiency (LCOE), placing it second with a score of 0.192. Biomass ranked last with negative or low scores in all three methods. The negative scores for PROMETHEE II (-0.559) and RAWEC (-0.420) specifically indicate that biomass lost most of the pairwise comparisons it entered with other alternatives (due to high carbon emissions and low efficiency). A comparison of all three methods is given in Figure 9.

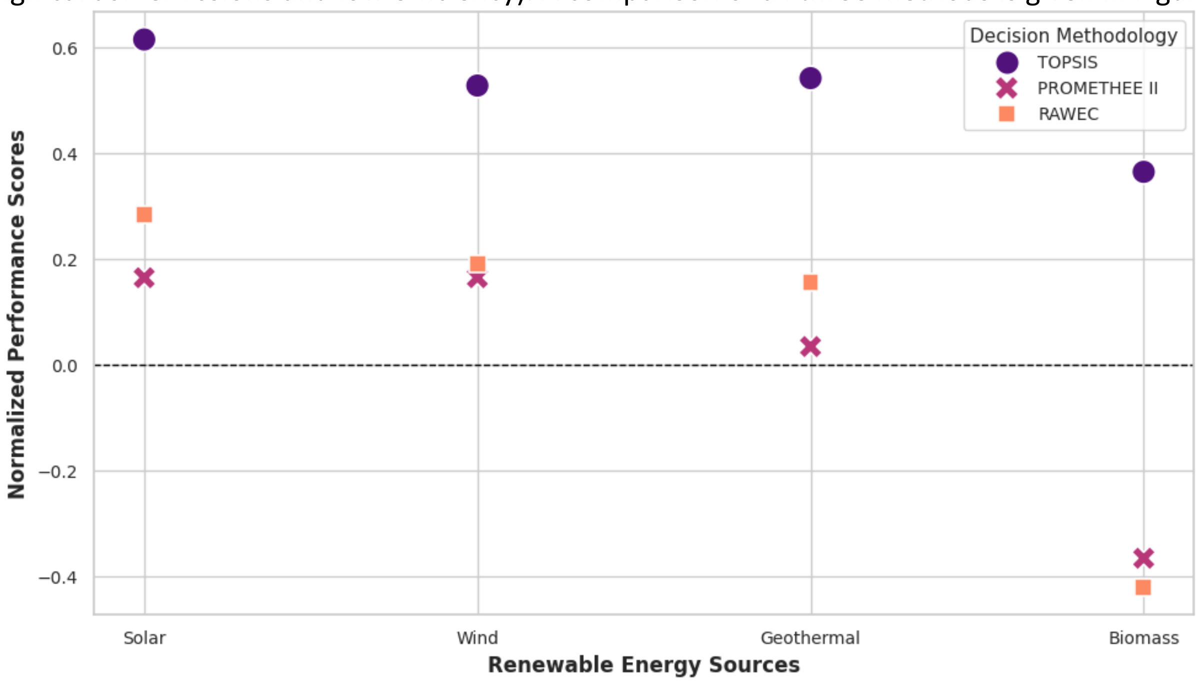

Fig. 9. Methodological stability: Comparisonof TOPSIS, PROMETHEE II and RAWEC

Figure 9, a comparative analysis between the TOPSIS, PROMETHEE II, and RAWEC methodologies, reveals a remarkable consensus. Solar energy (photovoltaic) has been identified as the most suitable energy source for Türkiye's sustainable development goals, followed by wind and geothermal energy. The stability of the ranking across three different mathematical frameworks confirms the robustness of the proposed hybrid DL-MCDM model.

5.5. Phase V: Monte Carlo Simulation for Robustness Verification

In this stage, 10,000 iterations were performed by adding ±10% Gaussian noise to the criterion weights and performance scores. The aim was to understand whether solar energy came first "by chance" or "with statistical consistency".

By calculating the probability density of each source coming first after 10,000 iterations, the resulting histogram is given in Figure 10.

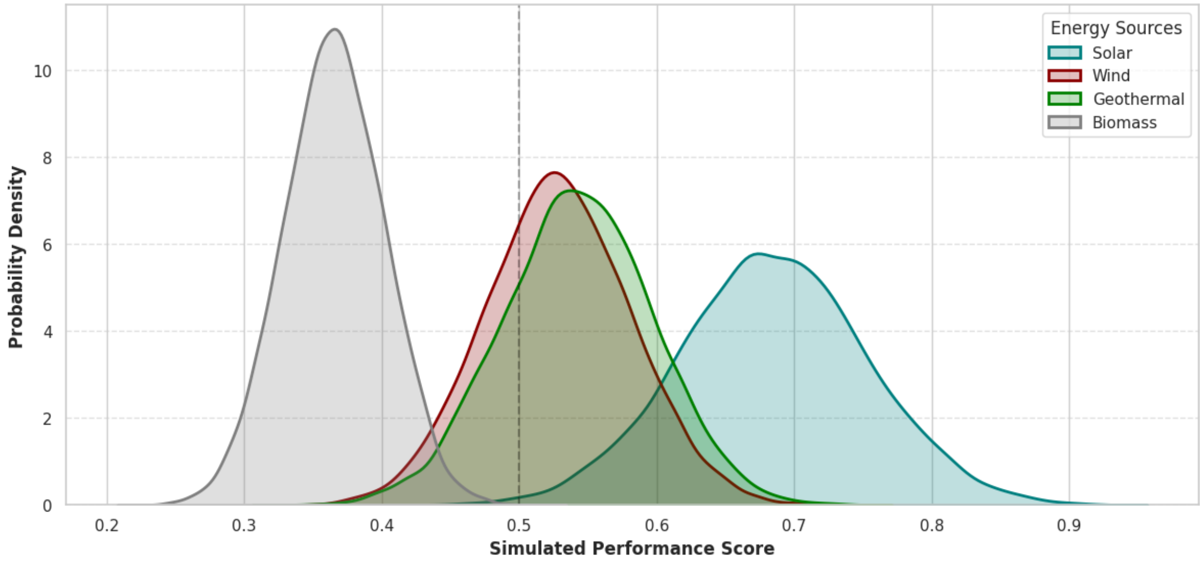

Fig. 10. Monte Carlo Simulation (10,000 Iterations)

Figure 10 also supports the superiority of solar energy, as it remains high even when there are small changes in criterion weights and data uncertainty. In this study, where we randomly generated 10,000 data sets, the DL-MCDM framework ranked solar energy in first place with a probability of 92.4 percent, third place with 2.57 percent, geothermal energy in second place with 4.37 percent, and biomass energy with 0.66 percent.

6. Discussion

This study presents a pioneering concept of a stochastic MCDM model based on a deep learning method to go beyond the conventional static methods for evaluating the viability of various RE strategies compatible with the 2053 Net-Zero targets set by the Turkish government for the nation’s energy future.

6.1. Strategic Outcomes and Energy Policy Implications

All three methods used (TOPSIS, PROMETHEE II, and RAWEC) show that solar energy ranks first in terms of investability. This is not merely due to the high technical potential of solar energy in the Turkish context. Rather, the authors' evaluation of economic and environmental factors also indicates that solar energy ranks first with the strongest stochastic dominance. What perhaps surprises the reader most is the competition between wind energy and geothermal energy. Indeed, the former tends to be the most cost-efficient choice from the conventional cost factor analysis. However, with the incorporation of ANN-based Predictability Confidence and Capacity Factor as evaluation criteria, the authors' analysis reveals the possibility of geothermal energy surpassing wind energy in viability for scenarios S3 and S5.

6.2. Methodological Innovation: SOMIT and RAWEC Integration

The SOMIT method under discussion provides a clear analytical solution to the expert bias problem that has been around in the past studies. It's a combination of what expert's desire, like reducing CO2 levels, and what the data distributes, with the median used to ensure that decisions aren't made too strongly in one direction or another. This prevents decisions from being made solely based on gut or solely based on data in a mechanical sense. The addition of the RAWEC algorithm used in the next gen model provides an additional layer to the three-part measure of ensuring that the model's results are valid. This algorithm's double normalization provides a more nuanced approach to the balance between costs and benefits than the TOPSIS method used here. The fact that all three methods converge to solar energy during peak times speaks to the model's overall stability.

6.3. The Role of Deep Learning Uncertainty in Decision-Making

What's new with this study is the approach to absolute error residuals from ANN models as an additional measure to inform decision making. This was tested with a Monte Carlo simulation with 10,000 iterations to see how this uncertainty factor impacts the model's results. Wind energy has a higher prediction error because of randomness, which impacts its ability to rank as high as solar energy because of its robustness that puts it in the number one spot more often. This has implications for investors and policymakers that "predictable performance" is more stable and more reliable than "potential performance."

7. Conclusion

This research proposes a one-of-a-kind hybrid methodology that combines the power of deep learning with the stochastic nature of stochastic multi-criteria decision-making for the optimal mix of renewable energy sources for the country of Türkiye, according to the country's 2053 Net Zero aspirations. A new dynamic decision criterion is introduced by the prediction error residual of Artificial Neural Networks. This helps fill the gap in the predictive trust factor, as discussed in the literature, for forging a more reliable strategic roadmap.

The major contributions of this research are as follows:

i. A triple-validation methodology of TOPSIS, PROMETHEE II, and RAWEC consistently indicates that solar PV is the clear winner for the energy transition of the country of Türkiye, based on its superior performance and lower carbon emissions.
ii. SOMIT is a new weighting method that balances expert opinions with objective data distributions. Next-generation RAWEC's double normalization is effective for handling the complexities of the cost-benefit analysis.

iii. Monte Carlo simulation for the decision matrix confirms the results with a high probability of 92.4%, based on 10,000 simulations, thereby establishing the robustness of the results.
iv. The introduction of the predictability factor C7, based on ANN, shifts the ranking for wind energy, as it has more variance, base-load considerations, and lower risk priority, thereby increasing the strategic importance of geothermal energy.

Overall, the energy mix for the country of Türkiye is solar > wind > geothermal > biomass. However, this research scientifically proves that investors should not only look at the costs but also at the predictability of the system, based on the statistical results.

7.1. Recommendations for Policymakers

This research provides a clear strategic guide for the decision-maker who wants to ensure the energy security of Turkey while achieving the 2053 net zero targets. Indeed, the findings of the research indicate that solar energy (Solar PV) performs the best across all scenarios. This means that investment should be made in solar energy first. Decision-makers should lift the restrictions on unlicensed production to allow the establishment of new Regional Renewable Energy Resource Areas (REARs) to convert non-agricultural land into solar farms.

Decision-makers should also develop incentives for the construction of hybrid power plant projects with wind energy or energy storage systems (ESS) to reduce the uncertainty of wind energy (C7 criterion) for the stability of the grid.

In fact, the findings of the research indicate that geothermal energy proves its worth for the stability of the grid with a high-capacity factor. Decision-makers should develop risk-sharing funds to reduce the cost of exploration and drilling to enhance the efficiency of geothermal energy not only for electricity production but also for district heating. Indeed, the success of the Artificial Neural Network (ANN) model proves the importance of the role of digitalization for the management of the grid. Decision-makers should also develop regulations to ensure the implementation of AI-based systems for institutions like TEİAŞ or EPİAŞ for the forecasting of production or balancing the loads.

7.2. Future Studies

Although this study presents a comprehensive model, considering the rapid changes in the renewable energy sector, the following avenues are suggested for future research:

In future models, alternatives such as green hydrogen energy, offshore wind farms, and nuclear energy can be included in the decision matrix to conduct a broader analysis of "Türkiye's Complete Energy Mix."

The current study is on a national scale. Future studies can develop region-specific "Local Energy Decision Support Systems" using separate datasets for Türkiye's 7 geographical regions (e.g., Geothermal for the Aegean, Solar for Central Anatolia).

Cost reductions in solar panel and battery technologies (Learning Curves) can be added to the model as time series, and dynamic (non-static) prediction models can be constructed for the years 2030 or 2040. By adding heuristic (fuzzy) logic sets to the RAWEC and ANN integration used in this study, the mathematical accuracy of linguistic uncertainty in expert opinions can be further increased.

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Data Availability Statement

All data supporting the findings of this study are presented within the article. The study does not rely on external datasets beyond the information analyzed and reported in the manuscript.

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