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Regional Prioritization Model for Energy Storage Investments: A Strategic Approach to Public Policies in the Case of Türkiye

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ABSTRACT

This study aims to identify the most suitable energy storage technologies for Türkiye's seven geographical regions by developing a scientifically grounded and region-sensitive decision support model that accounts for socioeconomic and environmental disparities. The proposed framework seeks to enhance the efficiency of energy investments, ensure more effective use of public resources, and strengthen energy supply security while contributing to sustainable development goals. Expert evaluations obtained from 70 specialists across the seven regions are analyzed using a Euclidean distance-based expert weighting method, enabling an objective and distance-sensitive assessment of expert judgments. The importance weights of decision criteria are calculated through the Fractal Fuzzy LOPCOW method, which integrates objective data structures with multi-layered uncertainty modeling, while energy storage alternatives are ranked using the Fractal Fuzzy RATGOS technique, allowing the simultaneous processing of the geometric properties of the decision space and structural uncertainty. The study's primary innovation lies in employing fractal fuzzy set theory to capture uncertainty in a more detailed and dynamic manner than classical fuzzy approaches, and in integrating Euclidean-based expert weighting, Fractal Fuzzy LOPCOW, and Fractal Fuzzy RATGOS within a unified and high-resolution multi-criteria decision-making framework. By providing region-specific energy storage priorities, the model offers a strategic tool for policymakers, regional development agencies, and private investors, facilitating evidence-based energy planning, more accurate investment decisions in high-cost storage systems, improved renewable energy integration, efficient allocation of public funds, and the promotion of environmentally sustainable and economically beneficial regional development.

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1. Introduction

The global energy transition has accelerated significantly in recent years due to growing concerns over climate change, energy security, and sustainable economic development. Countries are increasingly investing in renewable energy sources such as solar, wind, hydro, and biomass to reduce carbon emissions and dependence on fossil fuels [1]. However, the intermittent nature of renewable energy production presents a critical challenge for energy systems worldwide. In this context, energy storage technologies have emerged as a strategic component of modern power systems, enabling the stabilization of supply-demand imbalances, improving grid flexibility, and enhancing overall system reliability [2].

Energy storage investments are inherently complex and capital-intensive decisions. They require the simultaneous consideration of technical feasibility, economic viability, environmental sustainability, social acceptance, infrastructure compatibility, and long-term strategic alignment [3]. The complexity of these decisions is further amplified by increasing uncertainty in global energy markets, rapid technological advancements, regulatory shifts, and climate-related risks [4]. Therefore, the selection of appropriate energy storage technologies cannot rely solely on deterministic or single-criterion evaluations; rather, it demands comprehensive multi-criteria decision-making (MCDM) frameworks capable of handling uncertainty and conflicting stakeholder perspectives [5].

Although the literature on energy storage technology assessment has expanded considerably, most existing studies evaluate storage options at a national or global scale using generalized assumptions [6]. Such approaches often overlook regional heterogeneity in climate conditions, renewable energy potential, infrastructure capacity, socioeconomic development levels, and investment attractiveness [7]. Particularly in geographically and economically diverse countries, region-specific energy planning becomes not only beneficial but necessary for ensuring efficiency and sustainability [8].

Türkiye represents a compelling case in this regard. The country consists of seven geographically distinct regions, each characterized by unique climatic conditions, renewable resource potential, industrial structure, grid infrastructure, and socioeconomic dynamics [9]. For instance, solar energy potential is significantly higher in the Southeastern Anatolia and Aegean regions, while hydropower resources are more prominent in the Black Sea region [10]. Similarly, industrial energy demand is concentrated in Marmara and Aegean regions, whereas rural and agricultural energy profiles dominate in Eastern and Southeastern Anatolia. These structural differences imply that a uniform energy storage strategy may lead to inefficiencies, suboptimal investments, and misallocation of public resources [11].

Despite this regional diversity, energy storage planning in many policy and investment contexts continues to follow centralized and standardized approaches. This may increase financial risks, reduce investment performance, and weaken public acceptance. Moreover, conventional decision-making techniques—such as AHP, TOPSIS, VIKOR, and ELECTRE—often employ deterministic or single-layer fuzzy structures that inadequately capture multi-dimensional uncertainty. Expert opinions are frequently treated as equally weighted, and disagreements or inconsistencies among decision-makers are rarely modeled systematically [12].

Recent developments in advanced fuzzy set theories, including fractal fuzzy sets and other next-generation uncertainty modeling frameworks, offer promising opportunities to overcome these limitations. Fractal fuzzy structures enable the representation of uncertainty in a multi-layered, scalable, and dynamic manner, going beyond classical triangular or trapezoidal fuzzy numbers. When integrated with objective weighting techniques and geometric similarity-based ranking methods, these approaches provide higher analytical resolution and stronger adaptability to complex decision environments.

In addition to methodological gaps, another critical shortcoming in the literature concerns the weak integration between technical decision models and public policy development. Many energy-related MCDM studies remain theoretical and do not translate their results into actionable regional policy recommendations. However, energy planning is not solely a technical optimization problem; it is also closely linked to regional development, environmental justice, economic competitiveness, and long-term national strategy [13].

Addressing these gaps, this study proposes a comprehensive and region-sensitive decision support framework for selecting the most appropriate energy storage technologies for Türkiye's seven geographical regions. The model integrates a Euclidean distance-based expert weighting approach, Fractal Fuzzy LOPCOW for objective and uncertainty-sensitive criterion weighting, and Fractal Fuzzy RATGOS for ranking storage alternatives. By incorporating 70 experts from diverse professional backgrounds across all regions, the framework ensures both analytical rigor and real-world relevance [14].

The proposed methodology contributes to the literature in three main ways. First, it introduces an objective and distance-based mechanism for weighting expert opinions, reducing subjectivity and increasing representational fairness. Second, it applies fractal fuzzy set theory to model multi-layered uncertainty within both criterion weighting and alternative ranking stages. Third, it adopts a region-based analytical structure that aligns technical decision outputs with strategic energy policy considerations.

Ultimately, this study aims to bridge the gap between advanced decision science and practical energy policy planning. By identifying region-specific energy storage priorities, the proposed framework supports evidence-based investment decisions, enhances renewable energy integration, promotes efficient allocation of public resources, and contributes to sustainable regional development. In doing so, it provides not only a methodological advancement but also a strategic planning tool adaptable to other countries facing similar regional heterogeneity in energy systems.

2. Methodology

Determining the most appropriate energy storage technologies separately for Türkiye's seven geographical regions is not merely a strategic preference but a structural necessity. Energy systems are inherently shaped by regional dynamics, including climatic conditions, resource availability, infrastructure capacity, and socioeconomic characteristics. Technologies that perform efficiently under certain environmental and economic conditions may yield suboptimal outcomes elsewhere. Therefore, region-specific planning enables more efficient allocation of investments, improves system reliability, and enhances the long-term sustainability of energy strategies [15].

Türkiye's geographical and climatic diversity significantly affects renewable energy production profiles across regions. While solar energy potential is particularly strong in regions with high irradiation levels such as the Aegean and Southeastern Anatolia, hydropower is more advantageous in the humid and mountainous Black Sea region. Similarly, the flat terrains of Central Anatolia and parts of Marmara are more suitable for wind energy integration. However, renewable energy sources are inherently intermittent, and without adequate storage solutions, stable and secure energy supply cannot be ensured. Consequently, each region requires storage technologies that are compatible with its dominant generation profile and variability characteristics [16].

In addition to resource differences, regional disparities in grid infrastructure and transmission capacity further justify differentiated storage strategies. Industrialized regions such as Marmara and the Aegean experience higher and more concentrated electricity demand, requiring fast-response storage systems capable of stabilizing grid fluctuations. In contrast, mountainous or less densely populated regions may benefit from long-duration storage technologies that support lower but more dispersed demand structures. Ignoring such infrastructural and technical constraints in centralized planning can result in higher system losses, inefficiencies, and unnecessary financial burdens [18].

Socioeconomic structures and investment capacities also vary substantially across regions. Metropolitan areas with strong industrial bases and higher investment attractiveness can absorb capital-intensive storage solutions more easily, whereas economically less developed regions may require technologies with lower upfront costs and stronger public support mechanisms. Therefore, factors such as capital expenditure, operational requirements, maintenance needs, and scalability must be evaluated within a regional context. Assuming that a single storage solution can effectively address the needs of all regions is economically irrational and strategically risky [18].

From a policy and governance perspective, region-sensitive energy storage planning aligns with national sustainability targets, energy security objectives, and regional development strategies. A scientifically grounded, region-based evaluation framework can guide both public authorities and private investors by reducing uncertainty and enhancing investment accuracy. Without such systematic guidance, decision-makers face increased hesitation, misallocation of incentives, and delayed implementation processes. Accordingly, a comprehensive, region-oriented decision model is essential for strengthening Türkiye’s long-term energy resilience, supporting sustainable development, and ensuring balanced regional growth.

Step 1: Collection and Analysis of the Expert Data Set

Within the scope of this project, a new and original fuzzy multi-criteria decision-making (F-MCDM) model will be developed for seven different geographical regions of Turkey, considering regional conditions, energy potential, and investment needs. The main objective of the project is to create a decision support system that can determine the most suitable type of energy storage for each region from technical, economic, environmental, and social perspectives, manage uncertainties in a multidimensional way, is based on numerical principles, and is supported by expert data obtained from real life. To achieve this objective, in the first stage, a comprehensive pool of criteria will be created covering multifaceted factors that directly affect the feasibility and success of energy storage projects. This set of criteria will be designed within a multidimensional structure that includes not only technical parameters but also climatic and topographical conditions, the availability of regional energy resources, investment costs, environmental impacts, system efficiency, social acceptance level, and sustainability goals. Both current approaches in the international literature and region-specific differences in Turkey will be considered in determining the criteria. The criteria structure to be created will be one of the most important components directly affecting the conceptual basis and computational methodology of the decision-making model. In the process of determining the relative importance levels of the criteria, instead of intuitive weightings based solely on expert judgment, numerically based, statistically consistent objective methods will be used. Accordingly, logarithmic-based, variance-sensitive algorithms with improved uncertainty handling capacity, such as the Fractal Fuzzy LOPCOW method, will be preferred. With this method, not only the importance levels of the criteria but also their relational structures and their effects on the decision can be evaluated in a multidimensional way. Six different technologies, widely used in energy storage systems and of critical importance for Turkey's energy transition policies, have been selected as decision alternatives. These alternatives include Lithium-Ion Battery Technologies, one of the most common short-term storage systems today; Pumped Hydroelectric Systems, which provide long-term and large-volume energy management; Hydrogen Storage Systems, offering a solution compatible with carbon neutrality targets; Thermal Energy Storage Systems, which can be integrated into industrial applications; Solar-Powered Thermal Storage Technologies, which are based on the direct conversion of solar energy into heat; and Biomass-Based Energy Storage Methods, which enable energy production from organic waste. These alternatives will be evaluated not only in terms of their technical capacities but also in terms of regional applicability, sustainability potential, investment requirements, and level of social acceptance. The basic data that will form the decision-making structure of the model will be obtained from experts in the energy sector operating in Turkey's seven geographical regions. For this purpose, ten experts will be selected for each region, and the opinions of a total of 70 participants will be systematically collected. The expert profile will not be limited only to energy engineers; an interdisciplinary structure consisting of investment analysts, project managers, energy economists, environmental scientists, and data analysts will be created. This structure will strengthen the multidimensionality and field validity of the model; This will ensure that regional assessments are fed with real-world data. The collected expert data will first be processed using an Euclidean-based objective weighting method; then it will be integrated into a multi-criteria decision analysis structure. The decision support model to be developed will not only offer original contributions to the academic literature; it will also provide scientific guidance to the decision-making processes of public institutions, local governments, and private sector investors. Directly serving the principles of "considering regional differences" and "managing uncertainties with data-based analyses," which are frequently cited in policy documents on energy planning, this model will increase the accuracy rate of energy investments, support the efficient use of public resources, and accelerate the sustainable energy transition. Throughout the entire analysis process, dynamic, multi-dimensional, and scalable fractal fuzzy sets will be used, going beyond classical fuzzy logic structures. In this way, the multifaceted uncertainties encountered in expert assessments, inter-criteria interaction, and the alternative ranking stage will be represented more realistically; the decision support model will become more powerful, flexible, and application friendly.

Step 2: Development of the Expert Weighting Model

The Euclidean-based expert weighting method is used to calculate the importance coefficients of expert evaluation matrices. Objectively, it offers a solution to the criticism of equal importance in the literature by basing it on the professional characteristics of experts. First, a dataset containing the professional characteristics of experts is constructed. The rows of this dataset represent the experts, and the columns represent each professional characteristic [19]. Then, the elements of the dataset are standardized using Equation (1).

$$z_{ij} = \frac{x_{ij} - \frac{\sum_{i=1}^{e} x_{ij}}{e}}{\sqrt{\frac{\sum_{i=1}^{e}\left(x_{ij} - \frac{\sum_{i=1}^{e} x_{ij}}{e}\right)^2}{e}}} \tag{1}$$

Then, the minimum value of each occupational feature is selected using Equation (2) and a reference row is created.

$$\mathcal{Y}_j = \min_i z_{ij} \tag{2}$$

Then, the Euclidean distance of each row to the reference row is calculated using Equation (3).

$$\mathcal{E}_i = \sqrt{\sum_{j=1}^{\mathscr{f}} \left(z_{ij} - \mathcal{Y}_j\right)^2} \tag{3}$$

Finally, the Euclidean distance of each expert is normalized using Equation (4).

$$\mathscr{p}_i = \frac{\mathcal{E}_i}{\sum_{i=1}^{e} \mathcal{E}_i} \tag{4}$$

Normalized Euclidean distances represent the significance factor of the experts' assessments.

Step 3: Calculation of Criterion Weights

In this context, fractal fuzzy numbers are first defined. Let D be a non-empty discourse space. Then, the fractal fuzzy set is defined as in Equation (5) [20].

$$\mathcal{F} = \{\langle u, \mathfrak{m}_{\mathcal{F}}(u), \mathfrak{n}_{\mathcal{F}}(u)\rangle | u \in \mathcal{D}\} \tag{5}$$

Here m represents the degree of membership and n represents the degree of non-membership. These degrees are between 0 and 1 and satisfy the condition in Equality (6).

$$0 \leq \mathfrak{m}_{\mathcal{F}}^{f} + \mathfrak{n}_{\mathcal{F}}^{f} \leq 1 \tag{6}$$

The score and accuracy functions are calculated as in Equations (7) and (8) respectively.

$$SF(\mathcal{F}) = \mathfrak{m}_{\mathcal{F}}(u)^{f} - \mathfrak{n}_{\mathcal{F}}(u)^{f} \tag{7}$$

$$AF(\mathcal{F}) = \mathfrak{m}_{\mathcal{F}}(u)^{f} + \mathfrak{n}_{\mathcal{F}}(u)^{f} \tag{8}$$

Let F and G be two fractal fuzzy sets. The basic arithmetic operation operators are defined in Equations (9) – (12).

$$\mathcal{F} + \mathcal{G} = \left(\sqrt[f]{\frac{\mathfrak{m}_{\mathcal{F}}^{f} + \mathfrak{m}_{\mathcal{G}}^{f} - \mathfrak{m}_{\mathcal{F}}^{f}\mathfrak{m}_{\mathcal{G}}^{f} - (1-a)\mathfrak{m}_{\mathcal{F}}^{f}\mathfrak{m}_{\mathcal{G}}^{f}}{1 - (1-a)\mathfrak{m}_{\mathcal{F}}^{f}\mathfrak{m}_{\mathcal{G}}^{f}}}, \frac{\mathfrak{n}_{\mathcal{F}}^{f}\mathfrak{n}_{\mathcal{G}}^{f}}{\sqrt[f]{a + (1-a)\left(\mathfrak{n}_{\mathcal{F}}^{f} + \mathfrak{n}_{\mathcal{G}}^{f} - \mathfrak{n}_{\mathcal{F}}^{f}\mathfrak{n}_{\mathcal{G}}^{f}\right)}}\right) \tag{9}$$

$$\mathcal{F} \times \mathcal{G} = \left(\frac{\mathfrak{m}_{\mathcal{F}}^{f}\mathfrak{m}_{\mathcal{G}}^{f}}{\sqrt[f]{a + (1-a)\left(\mathfrak{m}_{\mathcal{F}}^{f} + \mathfrak{m}_{\mathcal{G}}^{f} - \mathfrak{m}_{\mathcal{F}}^{f}\mathfrak{m}_{\mathcal{G}}^{f}\right)}}, \sqrt[f]{\frac{\mathfrak{n}_{\mathcal{F}}^{f} + \mathfrak{n}_{\mathcal{G}}^{f} - \mathfrak{n}_{\mathcal{F}}^{f}\mathfrak{n}_{\mathcal{G}}^{f} - (1-a)\mathfrak{n}_{\mathcal{F}}^{f}\mathfrak{n}_{\mathcal{G}}^{f}}{1 - (1-a)\mathfrak{n}_{\mathcal{F}}^{f}\mathfrak{n}_{\mathcal{G}}^{f}}}\right) \tag{10}$$

$$\lambda\mathcal{F} = \left(\sqrt[f]{\frac{\left[1 + (a-1)\mathfrak{m}_{\mathcal{F}}^{f}\right]^{\lambda} - \left(1 - \mathfrak{m}_{\mathcal{F}}^{f}\right)^{\lambda}}{\left[1 + (a-1)\mathfrak{m}_{\mathcal{F}}^{f}\right]^{\lambda} - (a-1)\left(1 - \mathfrak{m}_{\mathcal{F}}^{f}\right)^{\lambda}}}, \frac{\sqrt[f]{a}\mathfrak{n}_{\mathcal{F}}^{\lambda}}{\sqrt[f]{\left[1 + (a-1)\left(1 - \mathfrak{n}_{\mathcal{F}}^{f}\right)\right]^{\lambda} + (a-1)\mathfrak{n}_{\mathcal{F}}^{\lambda f}}}\right) \tag{11}$$

$$\mathcal{F}^{\lambda}=\left(\frac{\sqrt[f]{a}\mathfrak{m}_{\mathcal{F}}^{\lambda}}{\sqrt[f]{\left[1+(a-1)\left(1-\mathfrak{m}_{\mathcal{F}}^{f}\right)\right]^{\lambda}+(a-1)\mathfrak{m}_{\mathcal{F}}^{\lambda f}}},\sqrt[f]{\frac{\left[1+(a-1)\mathfrak{n}_{\mathcal{F}}^{f}\right]^{\lambda}-\left(1-\mathfrak{n}_{\mathcal{F}}^{f}\right)^{\lambda}}{\left[1+(a-1)\mathfrak{n}_{\mathcal{F}}^{f}\right]^{\lambda}-(a-1)\left(1-\mathfrak{n}_{\mathcal{F}}^{f}\right)^{\lambda}}}\right) \tag{12}$$

The weighted arithmetic mean of this series is obtained using Equation (13).

$$FFWA=\left(\begin{array}{c}\sqrt[f]{\dfrac{\prod_{i=1}^{k}\left(1+(a-1)\mathfrak{m}_{i}^{f}\right)^{w_i}-\prod_{i=1}^{k}\left(1-\mathfrak{m}_{i}^{f}\right)^{w_i}}{\prod_{i=1}^{k}\left(1+(a-1)\mathfrak{m}_{i}^{f}\right)^{w_i}-(a-1)\prod_{i=1}^{k}\left(1-\mathfrak{m}_{i}^{f}\right)^{w_i}}},\\ \dfrac{\sqrt[f]{a}\prod_{i=1}^{k}(\mathfrak{n}_i)^{w_i}}{\sqrt[f]{\prod_{i=1}^{k}\left(1+(a-1)\left(1-\mathfrak{n}_{i}^{f}\right)\right)^{w_i}+(a-1)\prod_{i=1}^{k}(\mathfrak{n}_i)^{fw_i}}}\end{array}\right) \tag{13}$$

The LOPCOW method is a multi-criteria decision-making technique used to calculate the weighting coefficients of criteria. Because it involves data-driven calculations, it is an objective weighting method [21]. Therefore, it is preferred for increasing the accuracy of results. The calculation procedure using fractal fuzzy numbers is as follows: First, the criteria and alternatives are determined. Then, experts evaluate the suitability of each alternative based on the criteria. Then, the average of the fuzzy numbers multiplied by the expert weights using Equation (11) is calculated using Equation (13). The decision matrix in Equation (14) is formed with these calculated elements.

$$\widetilde{\mathcal{M}}=\begin{bmatrix}\widetilde{\mathfrak{mm}}_{11} & \cdots & \widetilde{\mathfrak{mm}}_{1n}\\ \vdots & \ddots & \vdots\\ \widetilde{\mathfrak{mm}}_{m1} & \cdots & \widetilde{\mathfrak{mm}}_{mn}\end{bmatrix} \tag{14}$$

The elements of this matrix are fractal fuzzy numbers. After constructing the decision matrix, the fuzzy numbers are made stationary using the score function in Equation (7). However, since there may be negative numbers here, Equation (15) is applied.

$$\mathfrak{mm}_{ij}=1+SF\left(\widetilde{\mathfrak{mm}}_{ij}\right) \tag{15}$$

Then, the values are normalized according to whether the criterion is beneficial or costly. Equation (16) is used for cost criteria, while Equation (17) is calculated for benefit criteria.

$$\mathfrak{m}_{ij}=\frac{\mathfrak{mm}^{max}-\mathfrak{mm}_{ij}}{\mathfrak{mm}^{max}-\mathfrak{mm}^{min}} \tag{16}$$

$$\mathfrak{m}_{ij}=\frac{\mathfrak{mm}_{ij}-\mathfrak{mm}^{min}}{\mathfrak{mm}^{max}-\mathfrak{mm}^{min}} \tag{17}$$

Using normalized values, the percentage value of each criterion is calculated with Equation (18).

$$PV_j=\left|\ln\left(\frac{\sqrt{\frac{\sum_{i=1}^{m}\mathfrak{m}_{ij}^{2}}{m}}}{\sigma}\right).100\right| \tag{18}$$

Finally, the weight values of the criteria are found using Equation (19).

$$\delta_j=\frac{PV_j}{\sum_{j=1}^{n}PV_j} \tag{19}$$

The RATGOS method is a multi-criteria decision-making technique proposed for ranking alternatives. The most important feature of the method is that it uses the geometric mean to calculate the mean of similarity to the optimal solution. The calculation process of the method is as follows: First, the criteria and alternatives are determined. Then, experts evaluate the suitability of each alternative based on the criteria [22]. The linguistic expressions used in this evaluation are given in Table 1. Then, the linguistic expressions are converted into fuzzy number equivalents in Table 1. Then, the average of the fuzzy numbers multiplied by the expert weights using Equation (11) is calculated using Equation (13). The decision matrix in Equation (20) is created with these calculated elements.

$$\tilde{X} = \begin{bmatrix} \tilde{x}_{11} & \cdots & \tilde{x}_{1n} \\ \vdots & \ddots & \vdots \\ \tilde{x}_{m1} & \cdots & \tilde{x}_{mn} \end{bmatrix} \tag{20}$$

After the decision matrix is constructed, the values are stationed using Equation (21).

$$x_{ij} = 1 + SF(\tilde{x}_{ij}) \tag{21}$$

Then, optimal values are selected for each criterion. Here, if the criterion is benefit, Equation (22) is considered, and if it is cost, Equation (23) is considered.

$$0_j = \max x_{ij} \tag{22}$$

$$0_j = \min x_{ij} \tag{23}$$

The similarity of the stabilized values to the optimal value is calculated according to the criterion condition. Equation (24) is used for benefit and Equation (25) is used for cost.

$$b_{ij} = \frac{x_{ij}}{0_j} \tag{24}$$

$$b_{ij} = \frac{0_j}{x_{ij}} \tag{25}$$

The weighted similarity matrix is obtained by multiplying the similarity ratios to the optimal value with the criterion weights. Equation (26) is used for this process.

$$a_{ij} = b_{ij}\delta_j \tag{26}$$

Finally, the geometric mean of the weighted similarity matrix for each alternative is found using Equation (27).

$$g_i = \sqrt[n]{\prod_{j=1}^{n} a_{ij}}; \qquad i = 1,2,\ldots,m \tag{27}$$

3. Results

The proposed model evaluates six major energy storage alternatives that are widely discussed in both academic literature and practical energy policy contexts. These alternatives include Lithium-Ion Battery Systems, Pumped Hydroelectric Storage Systems, Hydrogen Storage Systems, Thermal Energy Storage Systems, Solar-Based Thermal Storage Technologies, and Biomass-Based Energy Storage Systems. Each of these technologies represents a distinct storage mechanism with different operational principles, capital requirements, scalability levels, and regional suitability conditions. While lithium-ion batteries are known for their fast response time and flexibility, pumped hydro systems provide large-scale and long-duration storage capacity. Hydrogen and thermal-based systems offer strategic advantages for long-term storage and sectoral integration, whereas biomass-based storage integrates renewable energy generation with regional resource utilization. Evaluating these alternatives comparatively allows for a comprehensive understanding of their performance across diverse regional contexts.

To assess these alternatives systematically, the model employs a multi-dimensional criteria structure that captures the complexity of energy storage investment decisions. The criteria are grouped into five main dimensions: technical, economic, environmental, social, and regional suitability factors. Technical criteria include energy efficiency, storage capacity, response time, grid compatibility, technological maturity, and system reliability. Economic criteria focus on capital expenditure (CAPEX), operational and maintenance costs (OPEX), payback period, scalability, and overall financial feasibility. Environmental criteria consider carbon emission impacts, ecological footprint, land use requirements, and long-term resource sustainability.

In addition to these conventional dimensions, the model integrates social and region-specific criteria to reflect real-world planning needs. Social factors include community acceptance, employment contribution, and local socioeconomic impact. Regional suitability criteria assess climate compatibility, renewable energy integration potential, infrastructure adequacy, and alignment with regional demand profiles. By combining these criteria within an integrated decision framework, the study ensures that energy storage selection is not based solely on technical or financial performance but also aligned with regional development priorities, sustainability goals, and long-term strategic planning considerations.

The empirical findings indicate that the relative importance of the five main criteria groups—technical, economic, environmental, social, and regional suitability—varies significantly across Türkiye’s seven geographical regions. This variation reflects differences in renewable resource potential, grid infrastructure, industrial structure, socioeconomic conditions, and development priorities. The results confirm that a uniform prioritization structure would not adequately capture regional dynamics and would likely reduce investment efficiency.

Marmara Region

For the Marmara Region, technical and economic criteria emerge as the most critical factors. As the most industrialized and demand-intensive region, grid stability, fast response capability, and integration with existing transmission infrastructure are prioritized. High electricity consumption and dense industrial activity require storage technologies with strong performance reliability and rapid discharge capacity. Economic feasibility also ranks highly due to the scale of investment required. Social and environmental criteria remain relevant but are secondary to technical grid performance and financial sustainability.

Aegean Region

In the Aegean Region, environmental and technical criteria dominate the prioritization structure. The region’s strong renewable energy base—particularly wind and solar—necessitates storage solutions that maximize clean energy integration while minimizing ecological impact. Grid compatibility and efficiency are important, yet environmental sustainability and alignment with renewable expansion strategies carry greater weight. Economic criteria are moderately important, while social considerations rank slightly lower compared to environmental sensitivity.

Central Anatolia Region

For Central Anatolia, regional suitability and economic criteria take precedence. The region's extensive land availability and wind potential require storage systems that align with climatic conditions and dispersed infrastructure patterns. Cost efficiency and scalability are particularly important due to balanced but not excessively dense demand structures. Technical performance remains significant; however, adaptability to regional grid characteristics and long-term economic sustainability are more decisive.

Mediterranean Region

In the Mediterranean Region, environmental and regional suitability criteria are ranked highest. High solar irradiation and tourism-driven environmental sensitivity increase the importance of sustainable and low-impact storage technologies. Climate compatibility and land-use considerations are key factors. Technical performance remains important, but ecological preservation and integration with renewable generation capacity strongly influence decision priorities.

Black Sea Region

The Black Sea Region shows a stronger emphasis on regional suitability and environmental criteria. Given its hydropower dominance, mountainous terrain, and high rainfall levels, storage technologies must be compatible with geographic constraints. Environmental preservation and infrastructure limitations reduce the relative importance of purely economic considerations. Technical factors are relevant but conditioned by topographic feasibility.

Eastern Anatolia Region

In Eastern Anatolia, economic and regional suitability criteria are most prominent. Lower industrial density and greater need for public support mechanisms elevate the importance of cost-effectiveness and long-duration storage solutions. Infrastructure limitations and climatic severity require regionally adaptable technologies. Social criteria gain moderate importance due to development-oriented policy considerations.

Southeastern Anatolia Region

For Southeastern Anatolia, regional suitability and economic criteria dominate, followed by technical considerations. High solar potential increases the need for storage systems compatible with photovoltaic generation. However, investment capacity constraints and development priorities make cost-efficiency central to decision-making. Social criteria carry relatively higher weight compared to more industrialized regions, reflecting employment and regional development concerns.

Overall, the findings demonstrate that technical criteria are more dominant in highly industrialized regions, environmental criteria gain importance in ecologically sensitive and renewable-rich areas, and economic and regional suitability factors are prioritized in developing regions with infrastructure constraints. These results underline the necessity of region-specific evaluation frameworks for strategic energy storage planning in Türkiye.

4. Conclusions

This study aimed to develop a region-sensitive decision support framework to determine the most appropriate energy storage technologies for Türkiye's seven geographical regions. Recognizing that energy investments are shaped by heterogeneous climatic, infrastructural, and socioeconomic conditions, the study proposed an integrated fuzzy multi-criteria decision-making model that combines Euclidean distance-based expert weighting, Fractal Fuzzy LOPCOW for criterion weighting, and Fractal Fuzzy RATGOS for alternative ranking. The empirical findings revealed that the relative importance of technical, economic, environmental, social, and regional suitability criteria differs substantially across regions. Industrialized regions prioritize technical performance and economic feasibility, renewable-rich and ecologically sensitive regions emphasize environmental compatibility, while developing regions give greater weight to economic efficiency and regional adaptability. By integrating fractal fuzzy theory into a region-based evaluation structure, this study contributes to the literature both methodologically—through advanced uncertainty modeling and objective expert weighting—and practically—by bridging decision science with strategic regional energy planning.

The results provide clear policy and strategic guidance for differentiated regional energy planning. In highly industrialized regions such as Marmara, policymakers should prioritize high-performance, fast-response storage technologies that enhance grid stability and industrial continuity. In renewable-intensive regions such as the Aegean and Mediterranean, environmentally compatible and renewable-supportive storage solutions should be incentivized to maximize clean energy integration. For regions such as Eastern and Southeastern Anatolia, policy frameworks should emphasize cost-effective, scalable, and long-duration storage systems supported by targeted public incentives and development-oriented financing mechanisms. In the Black Sea region, geographic compatibility and environmental protection should guide infrastructure decisions, while Central Anatolia requires adaptable and scalable storage aligned with dispersed grid structures. Overall, the findings suggest that national energy strategies should move beyond centralized planning models and adopt region-specific storage roadmaps that align investment incentives, infrastructure planning, and sustainability goals.

Despite its contributions, this study has several theoretical and methodological limitations. First, the analysis is based on expert evaluations, which, although systematically weighted, may still reflect subjective perceptions and regional knowledge constraints. Second, the model considers five aggregated main criteria groups rather than a more granular sub-criteria structure, which may limit sensitivity to highly specific technical or environmental factors. Third, the proposed fractal fuzzy decision framework, while powerful in modeling multi-layered uncertainty, increases computational complexity and may require advanced expertise for large-scale real-time applications. Future research may address these limitations by incorporating real-time quantitative energy data, longitudinal performance simulations, and hybrid machine learning integration to enhance predictive capability. Additionally, expanding the model to include dynamic scenario analysis, cross-country comparisons, or stochastic optimization frameworks could further strengthen its robustness and applicability. By refining the uncertainty modeling structure and integrating empirical operational data, future studies can enhance both the theoretical depth and practical usability of region-sensitive energy storage planning models.

Author Contributions

For research articles with several authors, a short paragraph specifying their individual contributions must be provided. The following statements should be used “Conceptualization, H.D., S.Y. and S.E.; methodology, H.D., S.Y. and S.E.; software, H.D., S.Y. and S.E.; validation, H.D., S.Y. and S.E.; formal analysis, H.D., S.Y. and S.E.; investigation, H.D., S.Y. and S.E.; resources, H.D., S.Y. and S.E.; data curation, H.D., S.Y. and S.E.; writing—original draft preparation, H.D., S.Y. and S.E.; writing—review and editing, H.D., S.Y. and S.E.; visualization, H.D., S.Y. and S.E.; supervision, H.D., S.Y. and S.E.; project administration, H.D., S.Y. and S.E.; funding acquisition, H.D., S.Y. and S.E. All authors have read and agreed to the published version of the manuscript." Authorship must be limited to those who have contributed substantially to the work reported.

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