

Article

A Multi-Criteria Decision-Making Approach Integrated with Machine Learning for Energy Resource Supply

Erhan Baran 

Department of Electronic and Automation, TUSAS-Kazan Vocational School, Gazi University, Ankara 06980, Turkey; erhanbaran@gazi.edu.tr

Abstract

This study addresses the site selection problem for energy storage systems (ESSs) as a multi-criteria decision-making problem (MCDM) under conditions of uncertainty. First, potential candidate locations were identified using the K-means clustering algorithm based on the geographic coordinates of existing solar power plants (SPPs). As a result, six alternative locations representing spatial concentration were identified. These alternatives were then evaluated using the fuzzy TOPSIS method, a multi-criteria decision-making method (MCDM), taking into account the ten criteria defined for this study. Expert assessments were expressed and transformed into triangular fuzzy numbers to capture uncertainty and subjectivity in the decision-making process. The results show six alternative options, ranked from the one with the highest proximity coefficient to the one with the lowest. The findings demonstrate that the integrated use of machine learning (ML) and fuzzy TOPSIS methods provides an effective and robust decision support framework for ESS location selection problems. This approach also serves as a guide for other renewable energy planning practices.

Keywords: machine learning; multi-criteria decision-making; energy resource supply; supply chain management; fuzzy TOPSIS; k-means; solar energy systems

1. Introduction

The continuous increase in global energy demand has transformed the supply of energy resources into a multifaceted decision problem with strategic, economic, and environmental dimensions. Goals such as energy supply security, cost minimization, environmental reduction, and ensuring supply continuity often conflict with each other, complicating energy supply processes. This complexity makes approaches based on only a single criterion in energy resource supply insufficient, thus increasing the importance of multi-criteria decision making (MCDM) methods.

Traditional energy supply planning approaches are generally based on deterministic models and limited datasets [1]. However, the increasingly dynamic nature of energy markets, uncertainties in renewable energy production, and geopolitical risks necessitate the use of more flexible and data-driven methods [2]. In this context, big data analytics and machine learning (ML) techniques offer effective solutions in areas such as energy demand forecasting, price prediction, production planning, and risk analysis.

ML methods can model nonlinear relationships between numerous variables in energy systems and generate highly accurate predictions under conditions of uncertainty [3]. However, these methods often focus only on prediction and classification problems; the resulting outputs are not systematically evaluated to encompass the entire decision-making process. At



Academic Editors: Kristina Vaiciute and Aušra Katinienė

Received: 13 January 2026

Revised: 4 February 2026

Accepted: 11 February 2026

Published: 12 February 2026

Copyright: © 2026 by the author.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

this point, integrating predictions obtained through ML with MCDM methods enables more consistent, transparent, and rational decision-makings in energy resource supply [4].

MCDM approaches allow for the simultaneous evaluation of quantitative and qualitative criteria such as cost, environmental impact, security of supply, technological maturity, and social acceptance [5,6]. MCDM models, supported by ML, enable both more realistic determination of criterion weights and data-driven comparisons of the performance of alternative energy sources.

The aims of this study are to examine the combined use of ML and MCDM methods in energy resource procurement; to systematically review existing approaches in the literature; and to highlight the advantages of integrating these two methods. Furthermore, by evaluating application areas, challenges encountered, and future research trends, it aims to contribute to the development of data-driven and multi-dimensional decision support systems in the energy sector. The flowchart of this study is shown in Figure 1.

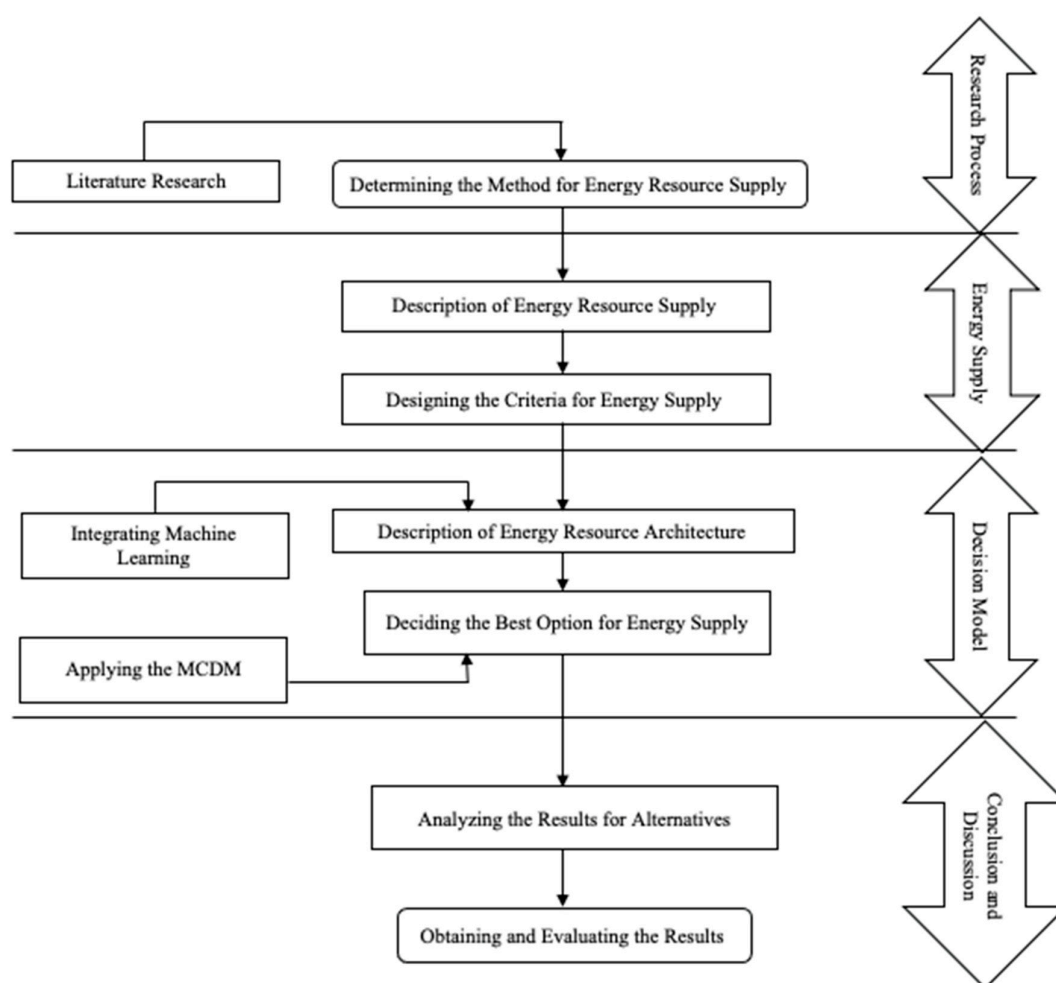


Figure 1. The flowchart of this study.

In this study, a large company in Ankara wants to utilize solar power plants (SPPs) to meet the energy needs of a new factory it plans to build. For this purpose, it wants to use an energy storage system (ESS). In this study, the K-means method was used to determine the locations of alternative ESSs. Based on criteria developed through a literature review and expert opinions, the fuzzy TOPSIS method was chosen to rank the alternatives. This study will enable a more effective approach to the decision-making process for energy supply. The combination of these methods and their application within this sector highlights the

originality of this study. The results obtained will also serve as a reference for future energy supply studies.

The main innovation of this study lies in the two-stage decision-making framework that integrates unsupervised machine learning and fuzzy multi-criteria decision-making. Unlike conventional site-selection studies that directly apply MCDM to predefined alternatives, this study first employs K-means clustering as a spatial pre-processing step to generate representative candidate locations based on the geographical distribution of existing solar power plants. The K-means algorithm is applied only once in this study. The elbow method is utilized to determine the optimal number of clusters by identifying the point at which the rate of decrease in the within-cluster sum of squares significantly slows down.

The Section 1 of this study provides an introduction and general information about the research. Section 2 presents the literature review conducted according to the methods to be studied. Section 3 examines the methods of supplying energy resources. The concept of supplying energy resources is explained in general. Section 4 describes the methods used in this study. The steps for implementing the methods are explained step by step. Section 5 shows the architectural structure created for the study. It explains how ML and fuzzy TOPSIS methods will be used in selecting and evaluating criteria. The ranking of alternative solar energy supply options is also presented.

2. Literature Research

This section systematically reviews the existing literature on the use of ML and MCDM methods in the field of energy resource supply. A framework for how the literature review was conducted is given in Figure 2.

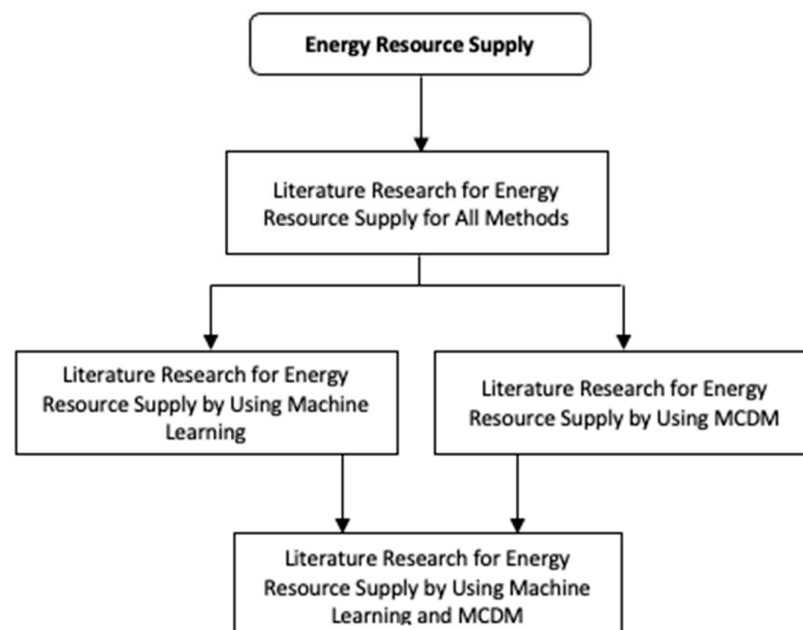


Figure 2. Literature review framework.

First, studies related to energy resource supply were generally searched. Wang and Lei (2023) conducted a study on energy supply from oil and natural gas in the United States [7]. Nunes et al. (2023) conducted a supply chain analysis regarding the conversion of woody waste biomass used in agroforestry into energy [8]. Their study used the PEST method and SWOT analyses. Bigerna et al. (2023) conducted an application in Italy on energy resource supply [9]. Other research on energy supply policies in Italy is available in the literature. Alhajri et al. (2023) [10] conducted a comprehensive study on the optimal planning of renewable energy sources to power water treatment units in Kuwait. They developed an

ML-based method for modeling uncertainties. Aboagye et al. (2021) conducted a study examining the status of renewable energy sources in electricity supply in Ghana [11]. Pinto et al. (2020) evaluated the potential of combining wave and solar energy sources to power offshore oil and gas platforms worldwide [12].

Many studies using ML in the energy field are included in the literature. Alhasnawi et al. (2025) [13] studied cyberattacks, cybersecurity, and energy management in smart grids using ML. The Internet of Things (IoT) was also used for the analyses. Alharbi et al. (2025) used ML for energy estimation of a building [14]. Allahyari et al. (2025) optimized energy use in underserved schools in hot and dry climates using ML [15]. Zhu et al. (2025) conducted a study on predicting carbon emissions in the energy sector based on noise reduction and hybrid ML [16]. Fasogbon et al. (2025) investigated optimizing the efficiency of an energy grid using the ML method [17]. Studies combining ML and deep learning (DL) algorithms can also be found in the literature. Tezcan and Efeoglu (2025) studied wind energy using ML and DL algorithms together [18]. Moon et al. (2025) used ML to evaluate the performance of interatomic potentials for energy estimation [19]. Mounika et al. (2025) used the ML method to predict power sharing in a fuel cell-based energy system [20]. Yan et al. (2025) used the ML method to minimize energy use [21]. Malakouti et al. (2025) conducted a study comparing the efficiency and accuracy of ML algorithms used to predict energy consumption across all sectors in the USA [22]. Tong et al. (2025) investigated the use of high-entropy materials with ML for advanced energy storage systems [23]. Rasouli and Rastegar (2025) conducted a study on combining DL, ML, and statistical methods with meta-learning to estimate net energy consumption in multiple carrier energy systems [24]. Abidin et al. (2025) conducted a systematic literature review on the combined use of IoT and ML for smart energy control in office buildings [25]. Aliqab et al. (2025) conducted an improvement study using the ML method for a graphene-based solar energy system [26]. Yadav et al. (2025) used the ML method to improve wind energy forecasts in India [27]. Lu and Wan (2025) used ML algorithms to estimate risk while investigating the causes of energy poverty among the Chinese population [28].

Studies using MCDM methods in the energy sector are also available in the literature. Pei et al. (2025) conducted an optimization study on energy saving using the fuzzy MCDM methods, preferring the fuzzy VIKOR and TOPSIS methods among them [29]. Shekari et al. (2025) used the MCDM approach in waste energy conversion, which involved AHP, ANP, and simple additive weighting methods [30]. Zournatzidou et al. (2025) used the TOPSIS method, a multi-criteria decision-making method, in their study on the analysis of energy efficiency [31]. Theiling et al. (2025) used AHP, ANP, and TOPSIS methods in energy-efficient building renovation [32]. Alhammadi et al. (2025) conducted a study to select an ESS; among the MCDM methods, AHP was preferred [33]. Roy et al. (2025) conducted a study using the TOPSIS method for selecting renewable energy systems [34]. Godoy et al. (2025) investigated energy planning in Ecuador using PROMETHEE, one of the MCDM methods [35]. Torres et al. (2025) conducted a study including AHP and TOPSIS methods for the selection of energy production technology in sustainable energy systems [36]. Amiri et al. (2024) similarly conducted a study on the selection of renewable energy sources in Saudi Arabia using the AHP and TOPSIS methods [37]. Liao and Li (2025) used the DEMATEL method, an MCDM method, for the selection of renewable energy storage technology [38]. Lotfipour and Mohtavipour (2024) used the AHP and TOPSIS methods together to determine the optimal share of renewable energy sources in the wholesale electricity market [39]. Liu et al. (2024) used the ARAS method, an MCDM method, for the problem of selecting a hybrid energy system focused on Industry 4.0 [40]. Uzair and Kazmi (2023) used the TOPSIS method for the analysis of the energy management system of smart buildings [41]. Gharibi et al. (2024) [42] conducted a study on the gasification

of polyethylene air considering energy and environmental aspects. They used ML and TOPSIS methods together in their study. Sadeghi et al. (2025) [43] conducted a comparison of renewable energy investments using MCDM methods. They used the TOPSIS, ELECTRE, and VIKOR methods for this comparison. Iglesias et al. (2025) used the AHP and VIKOR methods for the selection of energy production technologies [44]. Chung and Chang (2022) used data envelopment analysis, an MCDM method, for the analysis of hydrogen energy utilization in a fuzzy environment [45].

As a result of the literature review, many studies conducted in the field of energy were examined. A list of these studies, categorized by methodology, is shown in Table 1.

Table 1. List of studies in the energy field according to the methods used.

Research	Methodology	Objective
Nunes et al. (2023) [8]	PEST, SWOT	Converting waste biomass into energy
Alhajri et al. (2023) [10]	ML	To provide energy to water treatment units
Alhasnawi et al. (2025) [13]	ML and IoT	Cybersecurity and energy management
Alharbi et al. (2025) [14]	ML	Estimating the energy of a building
Allahyari et al. (2025) [15]	ML	Optimizing energy use in schools
Zhu et al. (2025) [16]	ML	Estimating carbon emissions in energy
Fasogbon et al. (2025) [17]	ML	Optimizing the efficiency of the energy grid
Tezcan and Efeoglu (2025) [18]	ML and DL	Wind energy optimization
Rasouli and Rastegar (2025) [24]	ML and DL	Energy consumption estimate
Abidin et al. (2025) [25]	ML and IoT	Smart energy monitoring in office buildings
Lu and Wan (2025) [28]	ML	Risk assessment for energy
Pei et al. (2025) [29]	Fuzzy VIKOR and TOPSIS	Energy saving optimization
Shekari et al. (2025) [30]	AHP and ANP	Waste energy conversion
Zournatzidou et al. (2025) [31]	TOPSIS	Energy efficiency analysis
Theiling et al. (2025) [32]	AHP, ANP, TOPSIS	Energy-efficient building renovation
Alhammadi et al. (2025) [33]	AHP	Selection of energy storage systems
Roy et al. (2025) [34]	TOPSIS	Selection of renewable energy systems
Godoy et al. (2025) [35]	PROMETHEE	Energy planning in Ecuador
Torres et al. (2025) [36]	AHP and TOPSIS	Selection of energy production technology
Amiri et al. (2024) [37]	AHP and TOPSIS	The selection of renewable energy systems
Liao and Li (2025) [38]	DEMATEL	Selection of energy storage technology
Lotfipour and Mohtavipour (2024) [39]	AHP and TOPSIS	Optimization of renewable energy sources
Liu et al. (2024) [40]	ARAS	Selection of energy systems
Uzair and Kazmi (2023) [41]	TOPSIS	Selection of energy systems management
Gharibi et al. (2024) [42]	ML and TOPSIS	Energy and environment
Sadeghi et al. (2025) [43]	TOPSIS, ELECTRE, VIKOR	Comparison of renewable energy systems
Iglesias et al. (2025) [44]	AHP and VIKOR	Selection of energy production systems
Chung and Chang (2022) [45]	Data Envelopment Analysis	Analysis of hydrogen energy

As seen in the literature review, most studies use only MCDM methods or only ML methods. Some publications use both ML and MCDM methods together. However, these publications do not focus on energy resource procurement.

In this study, the K-means clustering algorithm is employed as a spatial pre-screening tool to identify representative candidate locations for energy storage systems. Unlike previous studies that apply fuzzy TOPSIS directly to predefined alternatives, this study integrates an unsupervised clustering stage prior to the MCDM analysis.

This study involved the combined use of MCDM and ML methods in the field of energy resource supply. An application of this study was conducted at a leading company in its sector in Turkey. This research is unique in terms of the methods used and the sector in which it is applied. There is no similar study in the literature on solar energy supply. The

combined use of ML and MCDM methods is crucial for managing processes and ensuring the correct energy supply according to needs.

Despite the extensive literature on machine learning-based clustering and fuzzy MCDM methods, few studies have explicitly combined these approaches for energy storage system siting in the context of solar energy supply systems. Moreover, region-specific applications for Turkey remain limited. This study addresses these gaps by proposing an integrated ML–fuzzy TOPSIS framework grounded in a real-world industrial case.

3. Energy Resource Supply

Energy supply can be defined as the entirety of the processes and strategies followed by a country or a business to meet its energy needs in a secure, sustainable, and economical manner [46]. It can vary depending on the strategies of the countries or institutions [47]. Completing procurement processes requires making the right strategic decisions based on needs [48].

Energy supply can generally be classified according to the method of supply and the nature of the source [49]. Figure 3 shows the general framework of energy resource supply.

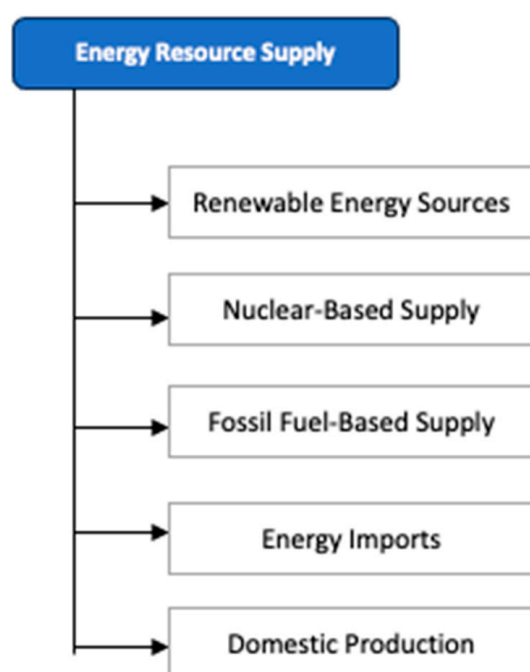


Figure 3. General framework of energy resource supply.

3.1. Supply Based on Renewable Energy Sources

Renewable energy supply can be defined as meeting energy needs through sources that are naturally renewable and have relatively low environmental impact [50]. Energy sources such as solar, wind, hydroelectric, geothermal, and biomass help increase energy supply security by reducing dependence on fossil fuels. The most fundamental advantage of renewable energy supply is its positive impact on reducing greenhouse gas emissions and combating climate change [51]. Energy supply based on renewable sources enables a balanced achievement of environmental sustainability, economic efficiency, and security of supply [52].

3.2. Nuclear-Based Supply

Nuclear energy supply relies on generating electricity using nuclear fuels such as uranium or thorium [53]. Thanks to its high energy density and uninterrupted production capacity, it holds a significant position in the sector [54].

3.3. Fossil Fuel-Based Supply

Energy supply based on fossil fuels refers to meeting energy needs through limited and non-renewable resources such as coal, oil, and natural gas [55]. Fossil fuels, which have formed the basis of global energy systems for many years, play a vital role in ensuring the continuity of energy supply owing to their high energy density and advanced infrastructure [56].

3.4. Supply Based on Energy Imports

Energy supply based on energy imports refers to a process where a country obtains all or a significant portion of its energy needs from foreign sources [57]. One of the main advantages of relying on energy imports is access to a higher capacity and greater variety of energy options compared to existing domestic sources. Long-term supply agreements, pipelines, and liquefied natural gas (LNG) infrastructure increase supply flexibility and ensure the continuity of energy systems [58].

3.5. Supply Based on Domestic Production

Energy supply based on domestic production refers to a country meeting its energy needs using its own natural resources, technological infrastructure, and production capacity [59]. The efficient use of domestic energy sources such as coal, hydroelectric, wind, solar, geothermal, and biomass is of strategic importance in terms of increasing energy supply security and reducing dependence on foreign sources [60]. In this study, the data based on domestic energy production in Turkey, the country where the application was used, for the year 2024 are shown in Table 2.

Table 2. Energy production data for Turkey in 2024.

Source Type	Percentage (%)
Hydraulic Energy	21.1
Wind Energy	10.4
Solar Energy	8.7
Geothermal Energy	3.1
Biomass	3.1
Total Renewable Energy	46.4
Fossil Fuels	53.6
Nuclear Energy	0

4. Materials and Methods

In this study, ML and MCDM methods were used together. The fuzzy TOPSIS method was used to weight the criteria and determine their importance levels. The K-means clustering method, one of the ML methods, was used to select the location of the ESS where energy supply is planned. All computational analyses were conducted using Python 3.10.11. K-means clustering was implemented using the scikit-learn library, while fuzzy TOPSIS calculations were performed using custom-coded scripts based on standard fuzzy arithmetic operations.

4.1. K-Means Clustering Method

K-means is a commonly used algorithm in unsupervised learning. It is an algorithm for dividing a dataset into K predetermined clusters [61]. The goal of this method is to minimize the sum of the distances of the data points within each cluster to their respective cluster centers [62]. In other words, it aims to maximize the similarity between observations within the same cluster while maximizing the difference between different clusters.

To mitigate the sensitivity of K-means clustering to initial centroid placement, the algorithm was executed multiple times with different random initializations, and the solution with the lowest within-cluster sum of squares was selected.

The steps to follow in applying the K-means method are as follows:

Step 1: Problem Definition and Notation

The dataset is defined as follows:

$$X = \{x_1, x_2, \dots, x_n\}, x_i \in \mathbb{R}^d \quad (1)$$

Here, n represents the number of data points, and d represents the size of each data point.

Step 2: Objective (Goal) Function

The objective function that the K-means algorithm attempts to minimize is:

$$J = \sum_{k=1}^K \sum_{x_i \in C_k} \|x_i - \mu_k\|^2 \quad (2)$$

Here, C_k represents the k -th set and μ_k represents the centroid of the k -th set.

Step 3: Determining the Number of Clusters (K)

The value of K is given independently of the problem.

$$K = \arg \min (WCSS(K)) \quad (3)$$

Here, WCSS (Within-Cluster Sum of Squares) represents the value of the objective function.

Step 4: Selecting Starting Centers

Initially, K centers are randomly selected:

$$\mu_1^{(0)}, \mu_2^{(0)}, \dots, \mu_K^{(0)} \quad (4)$$

Step 5: Assignment Step

Each data point is assigned to the nearest center:

$$C_i^{(t)} = \arg \min \|x_i - \mu_k^{(t)}\|^2 \quad (5)$$

Here, $c_i^{(t)}$ specifies the cluster label of x_i in the t -th iteration. This step ensures that the objective function is minimized while the centers are fixed.

Step 6: Update Step

For each cluster, the new center is calculated as the arithmetic mean of the points assigned to that cluster.

$$\mu_k^{(t+1)} = \arg \frac{1}{|C_k|} \sum_{x_i \in C_k} x_i \quad (6)$$

Here, $|C_k|$ represents the number of data points in the k -th cluster.

Step 7: Convergence Criterion

The algorithm stops when one of the following conditions is met:

$$\mu_k^{(t+1)} = \mu_k^{(t)}, \forall k \quad (7)$$

or

$$|J^{(t+1)} - J^{(t)}| < \varepsilon \quad (8)$$

The algorithm stops when it reaches the maximum number of iterations.

4.2. Fuzzy TOPSIS Method

The fuzzy TOPSIS method was chosen to enable the selection process by weighting and determining the importance levels of the criteria. Fuzzy TOPSIS can be defined as an adaptation of the classical TOPSIS method to decision problems involving uncertainty [63]. The aim of the method is to determine the alternative that is closest to the positive ideal solution and furthest from the negative ideal solution [64]. This method was chosen for the current study because it offers a more effective and faster solution in evaluating criteria and ranking alternatives. The application steps for the fuzzy TOPSIS method can be listed as follows:

Step 1: Problem Definition and Notation

$$A = \{A_1, A_2, \dots, A_m\}: \text{Alternatives} \quad (9)$$

$$C = \{C_1, C_2, \dots, C_n\}: \text{Criteria} \quad (10)$$

Next, the fuzzy criterion value x_{ij} and the fuzzy criterion weights w_j are calculated.

Step 2: Creating the Fuzzy Decision Matrix

A fuzzy decision matrix is created using the fuzzy criterion values X_{ij} .

Step 3: Normalizing the Fuzzy Decision Matrix

When creating a fuzzy decision matrix, separate calculations are performed for the Benefit Criterion and the Cost Criterion.

For the Benefit Criterion:

$$r_{ij} = \left(\frac{l_{ij}}{u_j^{max}}, \frac{m_{ij}}{u_j^{max}}, \frac{u_{ij}}{u_j^{max}} \right) \quad (11)$$

For the Cost Criterion:

$$r_{ij} = \left(\frac{l_j^{min}}{u_{ij}}, \frac{l_j^{min}}{m_{ij}}, \frac{l_j^{min}}{l_{ij}} \right) \quad (12)$$

Step 4: Weighted Normalized Fuzzy Decision Matrix

Each criterion is expressed with a fuzzy weight.

$$v_{ij} = r_{ij} \otimes w_j \quad (13)$$

Multiplication for triangular fuzzy numbers:

$$(l_1, m_1, u_1) \otimes (l_2, m_2, u_2) = (l_1 l_2, m_1 m_2, u_1 u_2) \quad (14)$$

Step 5: Determining Fuzzy Positive Ideal Solutions (FPIS) and Negative Ideal Solutions (FNIS)

$$A^+ = (\max u_{ij}) \quad (15)$$

Fuzzy Negative Ideal Solution (FNIS):

$$A^- = (\min l_{ij}) \quad (16)$$

Step 6: Distances of Alternatives from FPIS and FNIS

The distance between the peaks of two TFNs is calculated as follows:

$$d(a, b) = \sqrt{\frac{1}{3} [(l_a - l_b)^2 + (m_a - m_b)^2 + (u_a - u_b)^2]} \quad (17)$$

Distance from the positive ideal:

$$D^+_i = \sum_{j=1}^n d(v_{ij}, v_j^+) \quad (18)$$

Distance from the negative ideal:

$$D^-_i = \sum_{j=1}^n d(v_{ij}, v_j^-) \quad (19)$$

Step 7: Calculating the Proximity Coefficient

The dataset is defined as follows:

$$CC_i = \frac{D^-_i}{D^+_i + D^-_i} \quad (20)$$

The alternative with a higher CC_i is generally considered better.

Step 8: Ranking the Alternatives

$$A^* = \max(CC_i) \quad (21)$$

The alternatives are listed in descending order according to their CC_i values.

5. The Development of the Energy Resource Supply Decision Model

This study focuses on a project conducted within the scope of Ankara Province in Turkey, at one of the country's leading companies in its sector. This company wishes to use an ESS in Ankara to meet its energy needs.

In this study, 16 SPP alternative candidates located in Ankara were identified. After determining the locations of these alternatives, the K-means method and the elbow method were used to reduce the number of alternatives and perform clustering. Subsequently, the fuzzy TOPSIS method from the MCDM methods was used for six identified alternative options to determine the best alternative for ESSs.

To evaluate the criteria and alternatives in this study and achieve the most suitable energy supply, an architectural structure was created. The structure created is shown in Figure 4 as an energy source supply model.

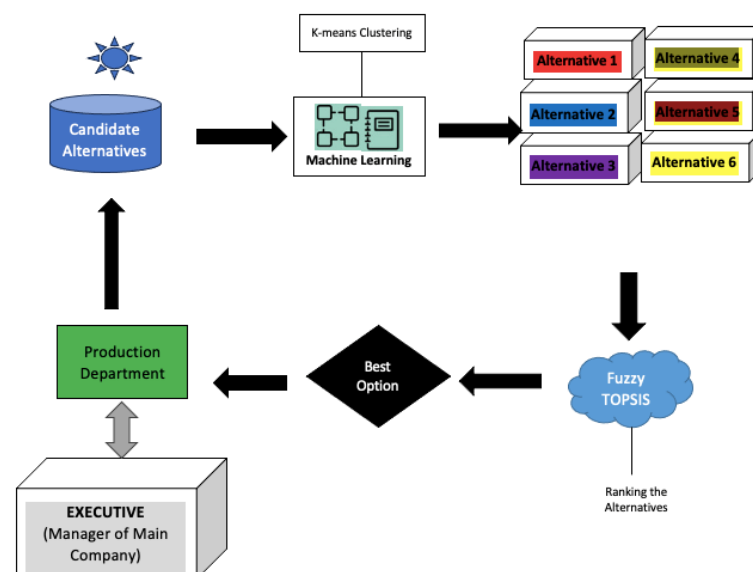


Figure 4. Energy resource supply decision model.

5.1. Solar Power Plants (SPPs)

The operating system of an SPP is shown in Figure 5.

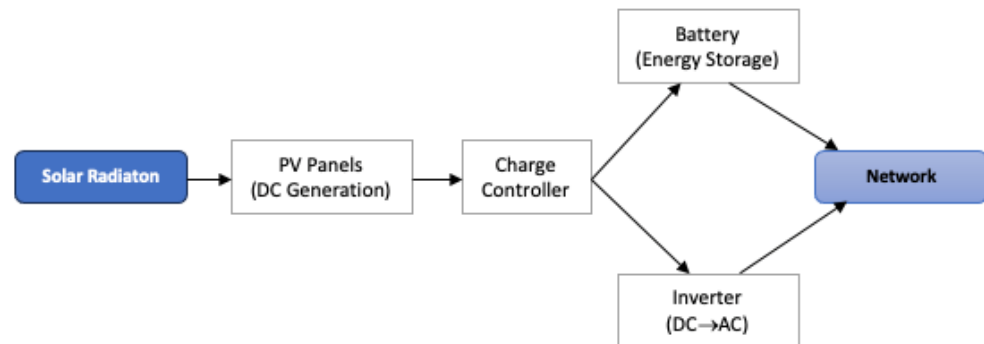


Figure 5. Diagram of an SPP's operation.

In this system, solar radiation is the primary energy source. Solar radiation is converted into direct current (DC) via photovoltaic panels. The DC produced here regulates the energy, thus preventing the battery from overcharging or discharging. Energy flow is routed between the battery and the inverter via a charge controller. Excess energy produced in the batteries is stored and released back into the system during periods of low production or peak demand. The DC energy from the battery is converted into alternating current (AC) compatible with the grid and loads via the inverter. The energy that enters the grid can be consumed directly. If there is excess energy, it can also be supplied to grid-connected systems.

5.2. Defining the Criteria

In this study, criteria were established for selecting an SPP and ensuring its energy supply, taking into account expert opinions and industry requirements. These criteria are shown in Table 3.

Table 3. Criteria for a solar power plant.

Criteria	Description	Type
C ₁	Sun exposure potential	Benefit
C ₂	Proximity to the network	Benefit
C ₃	Land cost	Cost
C ₄	Suitability for storage technology	Benefit
C ₅	Energy demand intensity	Benefit
C ₆	Environmental impact level	Cost
C ₇	Climatic risks	Cost
C ₈	Legal and administrative compliance	Benefit
C ₉	Accessibility in terms of transportation and logistics	Benefit
C ₁₀	Potential contribution to supply security	Benefit

Criterion C₁ represents the average annual global radiation level (kWh/m²-year). A higher value for this is preferred. The C₂ criterion refers to the distance to transformer substations. This distance is expected to be short. A shorter distance reduces connection costs. The C₃ criterion refers to land cost, expropriation, or rental costs. The C₄ criterion refers to the temperature, humidity, and environmental suitability of batteries. In this study, lithium-ion battery technology is assumed as the reference energy storage system due to its high energy density, technological maturity, and widespread adoption in industrial ESS applications. The C₅ criterion refers to the regional load profile and peak demand level. The C₆ criterion refers to the impact on ecosystems and agricultural areas. The C₇ criterion indicates risks such as extreme temperatures, floods, dust, and storms. The C₈ criterion

refers to zoning status, permit processes, and compliance with regulations. The C_9 criterion refers to equipment mobility, road and infrastructure conditions. Finally, the C_{10} criterion refers to the frequency of regional outages and the balancing capacity of storage.

5.3. Determining the Alternatives Using the K-Means Method

In this study, 16 alternative power plants were identified for the company. The geographical location coordinate data of the selected power plants were determined using Google Maps. These power plants were selected in close proximity to each other to overcome the problems arising from their existing capacities. The coordinates of these alternative SPPs are shown in Table 4.

Table 4. Geographical location coordinates of SSPs.

SPP _i	N	E
SPP ₁	39.0949	32.2393
SPP ₂	39.7843	32.3848
SPP ₃	39.9212	33.2840
SPP ₄	39.9659	32.5224
SPP ₅	39.6394	33.0556
SPP ₆	39.3796	32.0985
SPP ₇	39.5697	32.6682
SPP ₈	39.5349	33.1377
SPP ₉	40.0808	33.4264
SPP ₁₀	40.0512	32.1582
SPP ₁₁	38.9033	33.5716
SPP ₁₂	39.0967	32.2445
SPP ₁₃	39.7448	32.6135
SPP ₁₄	39.5501	33.1073
SPP ₁₅	39.7344	32.8022
SPP ₁₆	39.9683	32.5234

The geographical coordinates of 16 existing solar power plants were analyzed using the K-means clustering algorithm. Based on the elbow method, the optimal number of clusters was determined as $K = 6$. Figure 6 illustrates the spatial distribution of the solar power plants along with the resulting clusters and their centroids.

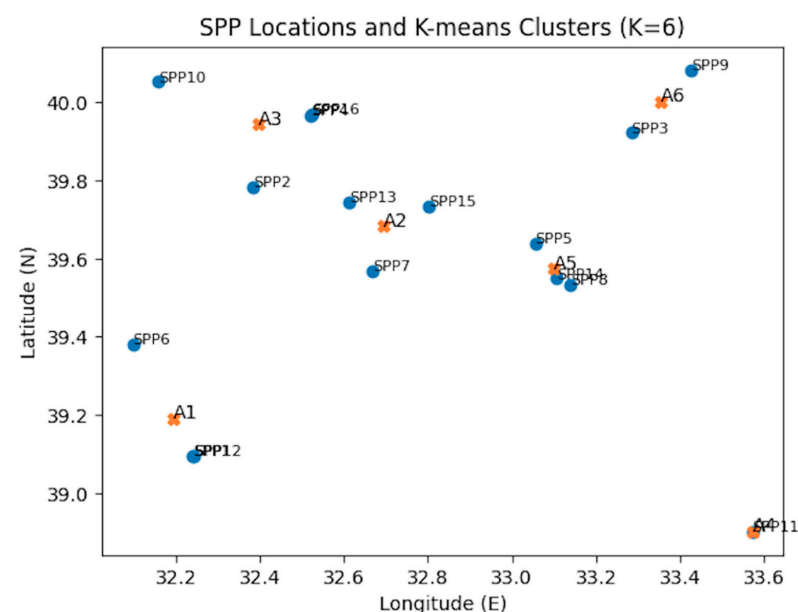


Figure 6. SPP locations and K-means clusters ($K = 6$).

Each cluster centroid represents a location with high spatial concentration of solar power generation and is therefore considered a candidate site for the installation of an energy storage system. This clustering-based pre-screening step effectively reduces the decision space and ensures that the subsequent evaluation focuses on spatially representative alternatives.

The six cluster centroids obtained from the K-means analysis are denoted as alternatives A_1 through A_6 . These alternatives capture the aggregated characteristics of nearby solar power plants and are assumed to be suitable candidates for ESS deployment, particularly in terms of minimizing transmission losses and enhancing local energy balancing.

The transformation of clustering outcomes into decision alternatives forms a critical link between machine learning and multi-criteria decision-making in the proposed framework, as summarized in Figure 6.

In the elbow method, the sum of the squares of the distances from the cluster center is calculated for the available k values. The inflection point where the difference between these squared sums begins to decrease is determined as the optimal k value based on the graph created from these sums.

The K-means clustering method can determine alternative locations for ESSs if it can cluster among an ideal number of options. To determine the number of alternative locations, the elbow method was used in this stage of the current study.

As a result of applying this method, the point closest to 0 as the inflection point is seen at the point where there are six alternative options.

After determining the number of alternative locations in this study, it is necessary to define the coordinate information for the ESS.

Each cluster centroid obtained from the K-means algorithm represents a spatially representative location that aggregates the characteristics of nearby solar power plants. These centroids are regarded as candidate alternative sites for energy storage systems, particularly in environmentally sensitive areas where installing storage facilities close to generation clusters may minimize transmission losses and land-use conflicts. Thus, the clustering results are transformed into decision alternatives for the subsequent fuzzy TOPSIS-based site selection stage.

The K-means clustering algorithm was used to make this identification. The coordinates of the identified ESS locations are shown in Table 5.

Table 5. The specified coordinates of the ESS.

Alternatives	N	E
A_1	39.09	32.24
A_2	39.38	32.10
A_3	39.74	32.61
A_4	39.63	33.11
A_5	39.94	32.52
A_6	40.05	33.43

Based on the clustering results, the next step is to evaluate the suitability of the identified candidate locations. Therefore, fuzzy TOPSIS is employed to rank these alternatives under multiple conflicting criteria.

5.4. Application of Fuzzy TOPSIS Method

In this study, after determining the alternatives using the K-means method, the fuzzy TOPSIS method was used to evaluate these alternatives by weighting them based on the 10 defined criteria. The ranking of the alternatives was also performed using fuzzy TOPSIS.

The expert evaluations were obtained from a panel of five experts, each having more than 10 years of professional experience in energy systems planning, renewable energy

integration, and grid operations. To ensure consistency and consensus, the individual assessments were aggregated using a consensus-based approach commonly adopted in fuzzy MCDM studies.

In the fuzzy TOPSIS method, the first step is to define the linguistic variables and triangular fuzzy numbers. These values are shown in Table 6.

Table 6. Linguistic variables and triangular fuzzy numbers (TFNs).

Linguistic Variables	TFN (l, m, u)
Very Low (VL)	(0.0, 0.0, 0.25)
Low (L)	(0.0, 0.25, 0.5)
Medium (M)	(0.25, 0.5, 0.75)
High (H)	(0.5, 0.75, 1.0)
Very High (VH)	(0.75, 1.0, 1.0)

The fuzzy decision matrix, created by evaluating alternatives based on criteria and expert assessment, is shown in Table 7.

Table 7. Fuzzy decision matrix.

Alternatives	C ₁	C ₂	C ₃	C ₄	C ₅	C ₆	C ₇	C ₈	C ₉	C ₁₀
A ₁	M	H	L	M	M	M	L	H	M	M
A ₂	H	M	M	H	M	M	M	M	H	M
A ₃	H	H	L	H	H	L	L	H	H	H
A ₄	M	M	M	M	M	M	M	M	M	M
A ₅	VH	H	L	VH	H	L	L	H	H	VH
A ₆	H	VH	L	H	H	L	M	VH	H	H

After the fuzzy decision matrix is created, the benefit criteria are divided by the maximum value. The cost criteria are divided by the minimum value. After normalization, all values are in the (0–1) range.

It is necessary to determine the fuzzy values of the criteria and continue with the steps. The fuzzy weights of the criteria are shown in Table 8.

Table 8. The fuzzy weights of the criteria.

Criteria	Weight (TFN)
C ₁	(0.7, 0.9, 1.0)
C ₂	(0.6, 0.8, 0.9)
C ₃	(0.5, 0.7, 0.9)
C ₄	(0.6, 0.8, 0.9)
C ₅	(0.6, 0.8, 0.9)
C ₆	(0.4, 0.6, 0.8)
C ₇	(0.4, 0.6, 0.8)
C ₈	(0.5, 0.7, 0.9)
C ₉	(0.5, 0.7, 0.9)
C ₁₀	(0.7, 0.9, 1.0)

A weighted normalized fuzzy decision matrix was created using the fuzzy values of the criteria and is shown in Table 9.

Table 9. Weighted normalized fuzzy decision matrix.

Alt.	C ₁	C ₂	C ₃	C ₄	C ₅
A ₁	(0.18, 0.45, 0.75)	(0.30, 0.60, 0.90)	(0.00, 0.18, 0.45)	(0.15, 0.40, 0.68)	(0.15, 0.40, 0.68)
A ₂	(0.35, 0.68, 1.00)	(0.15, 0.40, 0.68)	(0.15, 0.35, 0.68)	(0.30, 0.60, 0.90)	(0.15, 0.40, 0.68)
A ₃	(0.35, 0.68, 1.00)	(0.30, 0.60, 0.90)	(0.00, 0.18, 0.45)	(0.30, 0.60, 0.90)	(0.30, 0.60, 0.90)
A ₄	(0.18, 0.45, 0.75)	(0.15, 0.40, 0.68)	(0.15, 0.35, 0.68)	(0.15, 0.35, 0.68)	(0.15, 0.40, 0.68)
A ₅	(0.53, 0.90, 1.00)	(0.30, 0.60, 0.90)	(0.00, 0.18, 0.45)	(0.45, 0.80, 0.90)	(0.30, 0.60, 0.90)
A ₆	(0.35, 0.68, 1.00)	(0.45, 0.80, 0.90)	(0.00, 0.18, 0.45)	(0.30, 0.60, 0.90)	(0.30, 0.60, 0.90)
Alt.	C ₆	C ₇	C ₈	C ₉	C ₁₀
A ₁	(0.10, 0.30, 0.60)	(0.00, 0.15, 0.40)	(0.25, 0.53, 0.90)	(0.15, 0.40, 0.68)	(0.18, 0.45, 0.75)
A ₂	(0.10, 0.30, 0.60)	(0.10, 0.30, 0.60)	(0.15, 0.35, 0.68)	(0.25, 0.53, 0.90)	(0.18, 0.45, 0.75)
A ₃	(0.00, 0.15, 0.40)	(0.00, 0.15, 0.40)	(0.25, 0.53, 0.90)	(0.25, 0.53, 0.90)	(0.35, 0.68, 1.00)
A ₄	(0.10, 0.30, 0.60)	(0.10, 0.30, 0.60)	(0.15, 0.35, 0.68)	(0.15, 0.40, 0.68)	(0.18, 0.45, 0.75)
A ₅	(0.00, 0.15, 0.40)	(0.00, 0.15, 0.40)	(0.25, 0.53, 0.90)	(0.25, 0.53, 0.90)	(0.53, 0.90, 1.00)
A ₆	(0.38, 0.60, 0.70)	(0.10, 0.30, 0.60)	(0.38, 0.70, 0.90)	(0.25, 0.53, 0.90)	(0.35, 0.68, 1.00)

Weighted values were obtained by multiplying the normalized fuzzy decision matrix by the fuzzy weights of the criteria. For cost-related criteria (C₃, C₆, C₇), the normalization process may produce a zero lower bound when an alternative exhibits the minimum cost among all alternatives. This outcome is a direct result of the employed normalization technique and does not indicate data loss or numerical error. In the continuation of this study, the distances to the FPIS (1, 1, 1) and FNIS (0, 0, 0) values were found using these values. The total distances calculated are shown in Table 10.

Table 10. Calculated total distances.

Alternatives	D _i ⁺	D _i [−]
A ₁	5.12	4.31
A ₂	4.78	4.65
A ₃	3.95	5.32
A ₄	5.45	4.10
A ₅	3.62	5.88
A ₆	3.88	5.40

The calculated distance values were used to determine the proximity coefficient (CC_i) values, and the alternatives were ranked according to the calculated proximity coefficient values. The proximity values and final ranking are shown in Table 11.

Table 11. Proximity coefficient and final ranking.

Alternatives	CC _i	Rank
A ₅	0.619	1
A ₆	0.582	2
A ₃	0.574	3
A ₂	0.493	4
A ₁	0.457	5
A ₄	0.429	6

The ranking results demonstrate that superior performance in a single criterion is insufficient to guarantee optimality. Instead, alternatives achieving a balanced performance across multiple conflicting criteria tend to rank higher. In particular, the superior ranking of A₅ can be attributed to its strong performance in solar potential, grid proximity, suitability

for storage technology, and contribution to supply security, combined with relatively low environmental and climatic risks. Figure 7 shows the results of the Fuzzy TOPSIS.

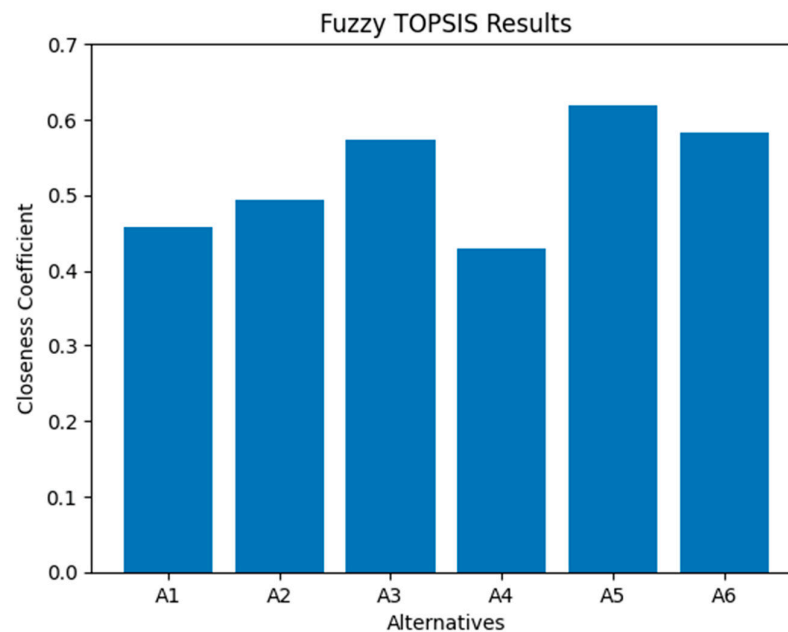


Figure 7. Fuzzy TOPSIS results.

Overall, the results confirm the effectiveness of the proposed ML–fuzzy TOPSIS framework in supporting complex ESS site selection decisions and highlight the importance of integrating spatial analysis with uncertainty-aware multi-criteria evaluation.

6. Discussion

The integrated decision-making framework proposed in this study differs from many approaches in the literature because it simultaneously addresses both spatial and multidimensional evaluation requirements in the site selection process of solar energy storage systems. Specifically, identifying alternatives using the K-means clustering method ensured that the decision-making process was based on a data-driven pre-selection phase rather than subjective constraints. This situation, along with reducing the number of alternatives to a reasonable level, has increased the computational efficiency of the fuzzy TOPSIS application.

An analysis of the fuzzy TOPSIS results reveals that while some alternatives perform well in specific criteria, they lag behind in the overall ranking. This situation reveals that not a single dominant criterion, but rather the balance and weighting of criteria, is decisive in site selection decisions. In particular, the combined assessment of criteria such as supply security, grid integration, and environmental impacts demonstrates that purely economic approaches may be limiting.

Unlike crisp TOPSIS, fuzzy TOPSIS allows for the incorporation of vagueness and uncertainty inherent in expert judgments, especially when evaluating qualitative criteria such as environmental impact, regulatory feasibility, and supply security. This is particularly important for energy storage system siting, where precise numerical data are often unavailable or highly uncertain. Thus, fuzzy TOPSIS provides a more realistic and flexible decision-making environment compared to its crisp counterpart.

The findings support the idea that considering uncertainty in energy storage investments improves decision quality. Evaluations using fuzzy numbers instead of precise values allowed for a more realistic reflection of differences in expert opinions in the model. However, the fact that criterion weightings are based on expert judgments can lead to

a certain degree of subjectivity in the results. This highlights the importance of using data-driven or ML-based weighting approaches in future studies.

Overall, the methodological framework developed within the scope of this study offers a powerful analytical tool for strategic decision-making processes regarding energy planning, storage systems, and renewable energy investments. The discussion results demonstrate that the proposed approach is adaptable to different regions, different energy technologies, and alternative sets of criteria.

7. Conclusions

This study addresses the MCDM problem, which involves uncertainty, in order to achieve the most suitable energy supply for solar energy storage systems. As part of this study, six alternative storage locations were first identified using the K-means clustering method with the geographical coordinates of existing SPPs. This approach has contributed to the rational creation of a set of alternatives by ensuring that density is taken into account in the decision-making process.

The alternatives identified within the scope of this study were evaluated using the fuzzy TOPSIS method. Linguistic evaluations based on expert opinions were integrated into the model with the help of triangular fuzzy numbers.

Based on the obtained proximity coefficients, alternative A5 was determined to be the closest to the positive ideal solution and the furthest from the negative ideal solution, and was therefore selected as the most suitable location for ESSs. The results obtained demonstrate that the integrated approach of K-means and fuzzy TOPSIS methods from ML is an effective decision support tool in energy supply and site selection problems. Future studies are recommended to determine criterion weights using ML-based methods and integrate real-time data into the model.

Funding: This research received no external funding.

Data Availability Statement: All data used in this study were generated within the scope of this research and are presented in this article. Therefore, there is no external data source or repository.

Acknowledgments: The author has reviewed and edited the output and take full responsibility for the content of this publication.

Conflicts of Interest: The author declare no conflicts of interest.

References

1. Bandejas, F.; Gomes, A.; Gomes, M.; Coelho, P. Multi-criteria sustainability assessment of energy resources in the energy supply chain of smart city ecosystems. *Energy Nexus* **2025**, *18*, 100441. [\[CrossRef\]](#)
2. Mun, K.G.; Cai, W.; Rodgers, M.; Choi, S. Optimizing multi-resource-based energy supply chains in developing economies: A periodic review model for affordable and sustainable solutions. *Comput. Ind. Eng.* **2024**, *192*, 110188. [\[CrossRef\]](#)
3. Badar, M.Z.I.; Al-Khalidy, M.M.M. Integrating blockchain and machine learning for secure energy transactions in smart grids. *Eng. Appl. Artif. Intell.* **2026**, *165*, 113419.
4. Parsa, S.M. Physics-informed machine learning meets renewable energy systems: A review of advances, challenges, guidelines and future outlooks. *Appl. Energy* **2025**, *402*, 126925. [\[CrossRef\]](#)
5. Sharma, T.; Sarin, A. Multi-criteria decision making for solar site selection in Punjab, India: An evaluation of site suitability using hybrid MCDM techniques towards the goal of sustainable energy development. *Results Eng.* **2025**, *27*, 106288. [\[CrossRef\]](#)
6. Baran, E.; Erol, S. A model suggestion to determine the order quantity in supplier selection problems. *Gazi Univ. J. Sci. Part A Eng. Innov.* **2014**, *3*, 45–50.
7. Wang, H.; Lei, Z. Energy supply from oil and gas, mineral depletion and total natural resource rents: Impact of oil equivalent energy use CO₂ intensity. *Resour. Policy* **2023**, *86*, 104172. [\[CrossRef\]](#)
8. Nunes, L.J.R.; Casau, M.; Dias, M.F.; Matias, J.C.O.; Teixeira, L.C. Agroforest woody residual biomass-to-energy supply chain analysis: Feasible and sustainable renewable resource exploitation for an alternative to fossil fuels. *Results Eng.* **2023**, *17*, 101010. [\[CrossRef\]](#)

9. Bigerna, S.; Ceccacci, F.; Micheli, S.; Polinori, P. Between saying and doing for ensuring energy resources supply: The case of Italy in time of crisis. *Resour. Policy* **2023**, *85*, 103782. [\[CrossRef\]](#)
10. Alhajri, I.; Ahmadian, A.; Alazmi, R. A comprehensive technical, economic and environmental evaluation for optimal planning of renewable energy resources to supply water desalination units: Kuwait case study. *Energy* **2023**, *275*, 127416. [\[CrossRef\]](#)
11. Aboagye, B.; Gyamfi, S.; Ofofu, E.A.; Djordjevic, S. Status of renewable energy resources for electricity supply in Ghana. *Sci. Afr.* **2021**, *11*, e00660. [\[CrossRef\]](#)
12. Pinto, S.O.; Santos, P.R.; Pinto, F.T. Assessment of the potential of combining wave and solar energy resources to power supply worldwide offshore oil and gas platforms. *Energy Convers. Manag.* **2020**, *223*, 113299. [\[CrossRef\]](#)
13. Alhasnawi, B.N.; Sadeq, A.M.; Homod, R.Z.; Hussain, F.F.H.; Sobeslav, V.; Bures, V. An extensive examination of cyberattacks, cybersecurity and energy management in smart grid, including new advancements and machine learning. *Energy Convers. Manag. X* **2025**, *29*, 101471. [\[CrossRef\]](#)
14. Alharbi, A.H.; El-kenawy, E.S.M.; Rizk, F.H.; Gaber, H.S.; Khafaga, D.S.; Eid, M.M. Optimized machines learning for building energy prediction: Feature selection and hyperparameter turning using the Al-Biruni earth radius search optimization algorithm. *Energy Rep.* **2025**, *14*, 5505–5538. [\[CrossRef\]](#)
15. Allahyari, S.; Khorram, Z.R.; Ahmadi, M.; Ahmadi, J.; Aram, F. Optimization of energy use and thermal comfort in underserved hot-dry climate schools using a machine learning framework. *Energy Rep.* **2025**, *14*, 4737–4749. [\[CrossRef\]](#)
16. Zhu, D.; Ma, R.; Liu, J.; Li, X.; Sha, J. A new method for predicting carbon emissions in energy industry based on CEEMD wavelet denoising and hybrid machine learning. *Energy Rep.* **2025**, *14*, 3132–3141. [\[CrossRef\]](#)
17. Fasogbon, S.K.; Fetuga, I.A.; Oyeniran, A.T.; Shaibu, S.A.; Afolabi, S.; Ndokwu, T.A.; Oluwadore, S.R.; Onafokowan, J.T.; Eso, O.S.; Bassey, V.B. Optimization of energy grid efficiency with machine learning: A comprehensive review of challenges and opportunities. *Renew. Sustain. Energy Rev.* **2025**, *223*, 115980. [\[CrossRef\]](#)
18. Tezcan, M.M.; Efeoglu, E. Electromagnetic torque prediction and modeling of a doubly fed induction generator for wind energy conversion systems using machine learning and deep learning algorithms. *Eng. Sci. Technol. Int. J.* **2025**, *72*, 102227. [\[CrossRef\]](#)
19. Moon, J.; Jeon, U.; Choung, S.; Han, J.W. CatBench framework for benchmarking machine learning interatomic potentials in adsorption energy predictions for heterogeneous catalysis. *Cell Rep. Phys. Sci.* **2025**, *6*, 102968. [\[CrossRef\]](#)
20. Mounika, K.; Goel, A.; Bhattacharjee, A. An accurate prediction of power sharing in a fuel-cell-based grid-interactive local energy system using machine learning techniques. *Int. J. Hydrogen Energy* **2025**, *196*, 152536. [\[CrossRef\]](#)
21. Yan, P.; Ren, B.; Ma, Y. Energy-minimizing generalized node network with machine learning optimization for complex fracture problems. *Eng. Appl. Artif. Intell.* **2025**, *162*, 112717. [\[CrossRef\]](#)
22. Malakouti, S.M.; Menhaj, M.B.; Suratgar, A.A. Efficiency and accuracy comparison of machine learning algorithms for predicting US energy consumption across sectors. *S. Afr. J. Chem. Eng.* **2025**, *54*, 424–440. [\[CrossRef\]](#)
23. Tong, X.; Sun, K.; Ye, H.; Cao, L.; Zhuang, J.; Tian, J.; Zhan, X. Recent advances in the high entropy materials for advanced energy storage with machine learning. *Mater. Rep. Energy* **2025**, *5*, 100379. [\[CrossRef\]](#)
24. Rasouli, A.; Rastegar, M. An ensemble of deep learning, machine learning and statistical methods stacked with meta-learning for forecasting net energy consumption in multi-carrier energy systems: Economic impact assessment. *Energy* **2025**, *340*, 139172. [\[CrossRef\]](#)
25. Abidin, A.Z.; Enriko, I.K.A.; Pramudita, A.A. Leveraging IoT, digital twin and machine learning for smart energy audit in office building: A systematic literature review and recommendations. *Adv. Electr. Eng. Electron. Energy* **2025**, *14*, 101124. [\[CrossRef\]](#)
26. Aliqab, K.; Agravat, D.; Alsharari, M.; Armghan, A.; Patel, S.K. Graphene-based solar absorber's potential for improved solar thermal energy conversion with optimization using machine learning. *Alex. Eng. J.* **2025**, *132*, 312–322. [\[CrossRef\]](#)
27. Yadav, H.K.; Chakraborty, S.; Gupta, M.N.; Bhattacharjee, A.; Yadav, S.; Sanyal, A.P.; Sarkar, J.; Sarkar, A. Enhancing wind energy forecasting in India: A site-specific comparative analysis of machine learning models and Weibull statistics using long-term data. *Sustain. Energy Technol. Assess.* **2025**, *84*, 104735. [\[CrossRef\]](#)
28. Lu, C.; Wan, S. Determinants of energy poverty among Chinese households: Risk prediction model using machine learning algorithms. *Energy* **2025**, *337*, 138502. [\[CrossRef\]](#)
29. Pei, S.; Chen, G.; Yao, J.; Dang, Y. Multi-objective optimization of residential energy-saving design based on fuzzy multi-criteria decision-making behavior model. *Case Stud. Therm. Eng.* **2025**, *74*, 106778. [\[CrossRef\]](#)
30. Shekari, A.; Shishebori, D.; Sadegheih, A.; Alidoosti, Z. Integrating energy justice principles in waste-to-energy conversion: A multi-criteria decision framework for sustainable urban waste management. *Sustain. Futures* **2025**, *10*, 101175. [\[CrossRef\]](#)
31. Zournatzidou, G.; Staikouras, C.; Ragazou, K.; Zopounidis, C.; Sariannidis, N. Unlocking the threshold effects of ESG performance towards policy energy efficiency of the European energy sector: A hybrid multi-criteria decision-making approach based on weight-entropy TOPSIS. *Energy Econ.* **2025**, *151*, 108915. [\[CrossRef\]](#)
32. Theiling, K.; Vollmer, M.; Lang, W.; Albus, J. Multi-criteria decision-making for energy building renovation: Comparing exterior wall structures with the AHP, ANP, utility analysis and TOPSIS. *Build. Environ.* **2025**, *280*, 113075.

33. Alhammadi, H.; Alghailani, M.; Alkhzaimi, N.; Alsuwaidi, D.; Mayyas, A. Multi-criteria decision-making methods for selecting the best energy storage systems in arid regions. *Energy Rep.* **2025**, *13*, 3575–3592. [\[CrossRef\]](#)
34. Roy, D.; Taghavifar, H.; Shivaprasad, K.V.; Wang, Y.; Das, B.K.; Roskilly, A.P. Multi-criteria decision-making and uncertainty analyses of off-grid hybrid renewable energy systems for an island community. *Energy Convers. Manag.* **2025**, *343*, 120120. [\[CrossRef\]](#)
35. Godoy, J.C.; Cajo, R.; Estrada, L.M.; Hamacher, T. Multi-criteria analysis for energy planning in Ecuador: Enhancing decision-making through comprehensive evaluation. *Renew. Energy* **2025**, *241*, 122278. [\[CrossRef\]](#)
36. Torres, J.A.H.; Lozano, D.S.; Herrera, R.S.; Vera, D.; Torreglosa, J.P. Integrated multi-criteria decision-making approach for power generation technology selection in sustainable energy systems. *Renew. Energy* **2025**, *243*, 122481.
37. Amiri, A.A.; Vahid, M.N.; Al-Buraiki, A.S.; Al-Sharafi, A. A strategic multi-criteria decision-making framework for renewable energy source selection in Saudi Arabia using AHP-TOPSIS. *Renew. Energy* **2024**, *236*, 121523. [\[CrossRef\]](#)
38. Liao, H.; Li, X. A multi-criterion decision making method for renewable energy storage technology selection with incomplete evaluation information. *Technol. Forecast. Soc. Change* **2025**, *215*, 124116. [\[CrossRef\]](#)
39. Lotfipour, A.; Mohtavipour, S.S. A multi-criteria decision-making model to determine the optimal share of variable renewable sources in a wholesale electricity market. *Sustain. Energy Grids Netw.* **2024**, *39*, 101408. [\[CrossRef\]](#)
40. Liu, P.; Eti, S.; Yuksel, S.; Dincer, H.; Gokalp, Y.; Ergun, E.; Aysan, A.F. Analyzing energy transition for industry 4.0-driven hybrid energy system selection with advanced neural network-used multi-criteria decision-making technique. *Renew. Energy* **2024**, *232*, 121081. [\[CrossRef\]](#)
41. Uzair, M.; Kazmi, S.A.A. A multi-criteria decision model to support sustainable building energy management system with intelligent automation. *Energy Build.* **2023**, *301*, 113687. [\[CrossRef\]](#)
42. Gharibi, A.; Babazadeh, R.; Hasanzadeh, R. Machine learning and multi-criteria decision analysis for polyethylene air-gasification considering energy and environmental aspects. *Process Saf. Environ. Prot.* **2024**, *183*, 46–58. [\[CrossRef\]](#)
43. Sadeghi, A.; Maleki, A.; Ahmadi, M.H.; Kiani, A.H. Comparative evaluation of renewable energy investments: A multi-criteria decision-making approach. *Energy Convers. Manag. X* **2025**, *28*, 101190. [\[CrossRef\]](#)
44. Iglesias, J.M.R.; Puente, J.; Fernandez, I.; Leon, O. A novel combined hybrid group multi-criteria decision-making model for the selection of power generation technologies. *Systems* **2025**, *13*, 742.
45. Chung, H.Y.; Chang, K.H. A novel general data envelopment analysis-based approach for MCDM issues of hydrogen energy under a fuzzy environment. *Systems* **2022**, *10*, 176. [\[CrossRef\]](#)
46. Eid, C.; Grosveld, J.; Hakvoort, R. Assessing the costs of electric flexibility from distributed energy resources: A case from the Netherlands. *Sustain. Technol. Assess.* **2019**, *31*, 1–8. [\[CrossRef\]](#)
47. Ma, T.; Javed, M.S. Integrated sizing of hybrid PV-wind-battery system for remote island considering the saturation of each renewable energy resource. *Energy Convers. Manag.* **2019**, *182*, 178–190. [\[CrossRef\]](#)
48. Baran, E.; Polat, T.K. Classification of industry 4.0 for total quality management: A review. *Sustainability* **2022**, *14*, 3329. [\[CrossRef\]](#)
49. Yilmaz, I.; Adem, A.; Dagdeviren, M. A machine learning-integrated multi-criteria decision-making approach based on consensus for selection of energy storage locations. *J. Energy Storage* **2023**, *69*, 107941. [\[CrossRef\]](#)
50. Zhao, C.; Song, X.; Yuan, X. Mitigating resource mismatches-oriented optimal cross-regional green hydrogen supply strategy considering cost and risk. *Transp. Res. Part E Logist. Transp. Rev.* **2025**, *204*, 104433. [\[CrossRef\]](#)
51. Afolabi, J.A. Towards carbon neutrality in Europe: The role of technology exports, renewable energy consumption, and resource productivity. *J. Environ. Manag.* **2025**, *395*, 127862. [\[CrossRef\]](#) [\[PubMed\]](#)
52. Zhang, L.; Liu, X.F. Sustainable development at the crossroads: Geopolitical risks, natural resource scarcity, and renewable energy in energy security transitions. *Geosci. Front.* **2025**, *16*, 102129. [\[CrossRef\]](#)
53. Luo, X.; Xia, J. Comparative analysis of zero-carbon supply solutions for mid-to-low temperature process heat using nuclear energy. *J. Clean. Prod.* **2024**, *469*, 143203. [\[CrossRef\]](#)
54. Kosai, S.; Unesaki, H. Nuclear power, resilience, and energy security under a vulnerability-based approach. *Clean. Energy Syst.* **2024**, *7*, 100107.
55. Heydenreich, T. Trade and decoupling of fossil fuel use embedded in EU consumption. *J. Clean. Prod.* **2024**, *464*, 142702. [\[CrossRef\]](#)
56. Harlan, T.; Baka, J. Stacked energyscapes: Conceptualizing fossil fuel and renewable energy entanglements in low-carbon transitions. *Energy Res. Soc. Sci.* **2024**, *115*, 103648. [\[CrossRef\]](#)
57. Lin, B.; Zhang, Z. Anchoring security in uncertainty: The dynamic responses of China's energy imports to geopolitical risk shocks. *Energy* **2025**, *335*, 137996. [\[CrossRef\]](#)
58. Eschmann, J.; Jochem, P. Assessing import dependencies in the accelerating energy transition: A structural gravity model analysis. *Energy Policy* **2025**, *205*, 114697. [\[CrossRef\]](#)
59. Galimova, T.; Fasihi, M.; Bogdanov, D.; Lopez, G.; Breyer, C. Analysis of a green e-methanol supply costs: Domestic production in Europe versus imports via pipeline and sea shipping. *Renew. Energy* **2025**, *241*, 122336. [\[CrossRef\]](#)

60. Ulrich, O.; Morsch, P.; Peschel, A. Decentralized use case integration of chemical hydrogen carriers: The cost saving potential in domestic supply chains. *Int. J. Hydrogen Energy* **2025**, *186*, 151928. [[CrossRef](#)]
61. Song, Z.; Cai, J.; Yang, Q. Taxi travel distance clustering method based on exponential fitting and k-means using data from the US and China. *Systems* **2024**, *12*, 282. [[CrossRef](#)]
62. Hung, C.Y.; Wang, C.C. An approach for multi-item product sales forecasting based on advancing the BCG matrix with matrix-clustering and time modeling techniques. *Systems* **2024**, *12*, 388. [[CrossRef](#)]
63. Baran, E. An innovative fuzzy TOPSIS method to determine the location of a new hospital. *Int. J. Eng. Sci. Appl.* **2018**, *2*, 133–136.
64. Yang, Y.; Zhang, K.; Lei, Z. A consensus reaching process for product design decision-making by integrating intuitionistic fuzzy sets and trust network. *Systems* **2024**, *12*, 494. [[CrossRef](#)]

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.