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Evaluating AI-Based Energy Management Strategies for Electric Vehicles using SWARA - weighted Pythagorean Fuzzy MULTIMOORA

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Anahtar Kelimeler

Enerji Yönetimi
Elektrikli Araçlar
Yapay Zeka
Çok Kriterli Karar Verme
Pisagor Bulanık Kümeler

Graphical/Tabular Abstract (Grafik Özet)

This study applies a SWARA–weighted Pythagorean Fuzzy MULTIMOORA framework to evaluate AI-based energy management strategies for electric vehicles, with the results validated through sensitivity and comparative analyses. / Bu çalışmada, elektrikli araçlar için yapay zekâ tabanlı enerji yönetim stratejilerini değerlendirmek amacıyla SWARA–ağırlıklı Pisagor Bulanık MULTIMOORA yöntemi uygulanmakta ve elde edilen sonuçlar, duyarlılık ve karşılaştırmalı analizler ile doğrulanmaktadır.

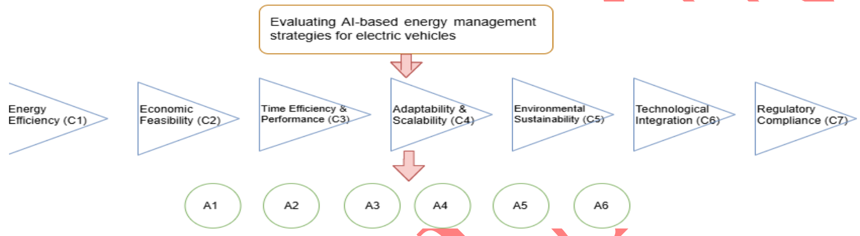

***Figure A**:Hierarchical Structure /**Şekil A**:.Hiyerarşi Yapısı*

Highlights (Önemli noktalar)

- *Development of a SWARA–weighted Pythagorean Fuzzy MULTIMOORA framework for evaluating AI-based energy management strategies in electric vehicles. / Yapay zekâ tabanlı EV enerji stratejileri için SWARA–ağırlıklı Pisagor Bulanık MULTIMOORA yönteminin geliştirilmesi*
- *Top strategies: Smart Battery Management, Predictive Energy Optimization, AI-Enabled Smart Charging / En iyi stratejiler: Akıllı Batarya Yönetimi, Tahmine Dayalı Enerji Optimizasyonu, Yapay Zekâ Tabanlı Akıllı Şarj*
- *Validation of results through 21-scenario sensitivity analysis and comparative analysis with the Pythagorean Fuzzy TOPSIS method. / Sonuçlar 21 senaryolu duyarlılık analizi ve Pisagor Bulanık TOPSIS kullanılarak yapılan karşılaştırma analizi ile doğrulanmıştır.*

Aim (Amaç): *The aim of this study is to comprehensively evaluate AI-based energy management strategies for electric vehicles to enhance efficiency, extend battery life, and promote the use of sustainable energy sources. / Bu çalışmanın amacı, elektrikli araçlarda yapay zekâ tabanlı enerji yönetim stratejilerini değerlendirerek verimliliği artırmak, batarya ömrünü uzatmak ve sürdürülebilir enerji kaynaklarının kullanımını teşvik etmektir.*

Originality (Özgünlük): *This study is original in providing a comprehensive framework that prioritizes AI-based energy management strategies for electric vehicles using a structured hybrid method, addressing the gap left by most studies that focus only on isolated aspects without in-depth AI strategy evaluation. / Bu çalışma, yapay zekâ tabanlı enerji yönetimi stratejilerini önceliklendiren yapılandırılmış bir hibrit yöntem sunarak, çoğu çalışmanın yalnızca tekil alanlara odaklanıp AI stratejilerini derinlemesine değerlendirmemesi nedeniyle oluşan boşluğu doldurmaktadır.*

Results (Bulgular): *Smart Battery Management Systems emerged as the top AI-based energy strategy, followed by Predictive Energy Optimization and AI-Enabled Smart Charging, with 21-scenario sensitivity analysis and PF-TOPSIS comparison confirming the robustness, stability, and reliability of the proposed hybrid framework. / Akıllı Batarya Yönetimi ilk sırada öne çıkarken, Tahmine Dayalı Enerji Optimizasyonu ve Yapay Zekâ Tabanlı Akıllı Şarj ikinci ve üçüncü sırada yer almakta; 21 senaryolu duyarlılık analizi ve PF-TOPSIS karşılaştırması, önerilen hibrit yöntemin sağlamlığını ve güvenilirliğini doğrulamaktadır.*

Conclusion (Sonuç): *This study provides actionable insights to guide engineering professionals and promote the adoption of sustainable energy solutions. / Bu çalışma, mühendislik profesyonellerine yol gösteren ve sürdürülebilir enerji çözümlerinin benimsenmesini destekleyen uygulanabilir bilgiler sunmaktadır.*

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Abstract

The growing adoption of electric vehicles (EVs) has formed a pressing need for intelligent energy management systems to extend battery life, improve efficiency and encourage the use of sustainable energy sources. As the complexity of energy optimization increases, the integration of artificial intelligence (AI) has become essential for enabling real-time decision-making and adaptive control. However, a significant gap remains in the literature regarding the comprehensive evaluation and prioritization of AI-based energy management strategies for EVs. This study addresses this gap by developing a multi-criteria decision-making (MCDM) framework that combines the Stepwise Weight Assessment Ratio Analysis (SWARA) method to determine the importance of evaluation criteria with the Pythagorean Fuzzy MULTIMOORA method to rank alternative strategies. The results show that Smart Battery Management Systems is the most critical strategy, followed by Predictive Energy Optimization and AI-Enabled Smart Charging and Grid Integration. A sensitivity analysis involving 21 weight variation scenarios confirms the robustness and stability of the suggested model. The findings offer practical insights for policymakers and professionals in engineering and present a flexible methodological framework that can be applied to other complex decision-making problems in sustainable energy and transportation systems.

Elektrikli Araçlar için Yapay Zekâ Tabanlı Enerji Yönetim Stratejilerinin SWARA Ağırlıklı Pisagor Bulanık MULTIMOORA Yöntemi ile Değerlendirilmesi

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Öz

Elektrikli araçların yaygınlaşması, verimliliği artırmak, batarya ömrünü uzatmak ve yenilenebilir enerji kaynaklarını entegre etmek amacıyla akıllı enerji yönetim sistemlerine olan ihtiyacı artırmıştır. Artan karmaşıklık karşısında, yapay zekâ entegrasyonu gerçek zamanlı karar verme ve uyarlanabilir kontrol açısından büyük önem taşımaktadır. Ancak literatürde, elektrikli araçlar için yapay zekâ tabanlı enerji yönetim stratejilerinin kapsamlı şekilde değerlendirilmesine yönelik sınırlı çalışma bulunmaktadır. Bu çalışmada, değerlendirme kriterlerinin önemini belirlemek için SWARA, stratejileri önceliklendirmek için Pisagor Bulanık MULTIMOORA yöntemlerinin entegre edildiği çok kriterli karar verme tabanlı bir model geliştirilmiştir. Bulgulara göre, "Akıllı Batarya Yönetim Sistemleri" en öncelikli strateji olarak belirlenmiş, ardından "Tahmine Dayalı Enerji Optimizasyonu" ve "Yapay Zekâ Tabanlı Akıllı Şarj ve Şebeke Entegrasyonu" gelmiştir. Yirmi bir senaryoda yapılan duyarlılık analizi, modelin sağlamlığını ortaya koymuştur. Elde edilen sonuçlar, politika yapıcılar ve mühendislik uzmanları için stratejik karar alma süreçlerinde yol gösterici niteliktedir.

1. INTRODUCTION (GİRİŞ)

The transportation sector remains one of the largest consumers of energy globally, with a significant portion of this demand being met by fossil fuels such as natural gas, oil, coal. This substantial fossil fuel dependence is a major contributor to greenhouse gas emissions, air pollution, and the acceleration of climate change. The growing scarcity of fossil fuels has led to increased energy costs and raised concerns about long-term economic stability, particularly for nations heavily dependent on energy imports [1]. In response to these challenges, the global focus has shifted toward cleaner, more energy-efficient alternatives, with

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electric vehicles (EVs) emerging as a key solution. By decreasing the release of carbon and making possible to include sources of clean energy, EVs play a vital role in reshaping the future of transportation toward greater sustainability and energy independence.

According to recent data from Eurostat (2025) [2], the transportation industry accounted for 31.0% of the EU's ultimate energy usage in 2022, highlighting its significant role in overall energy demand. Within this sector, road transport alone consumed 73.6% of the total energy used, with the vast majority—90.6%—originating from fossil fuels such as motor oil with gasoline or diesel. As shown in Figure 1, the dominance of gas/diesel oil has steadily increased since 1990, overtaking motor gasoline as the primary energy source in road transport. Although electricity usage remains marginal at just 0.3% in 2022, it has seen a noticeable upward trend, increasing more than six-fold between 2018 and 2022. This modest but promising growth indicates a gradual shift toward electrification in transport. Simultaneously, electricity prices across the EU have shown mixed trends—with some countries like Ireland experiencing steep increases, while others, such as the Netherlands, have seen notable reductions. For non-household consumers, the average electricity price dropped by 13% in the first half of 2024 compared to the same period in 2023, signaling improved conditions for commercial and industrial electric vehicle usage [3].

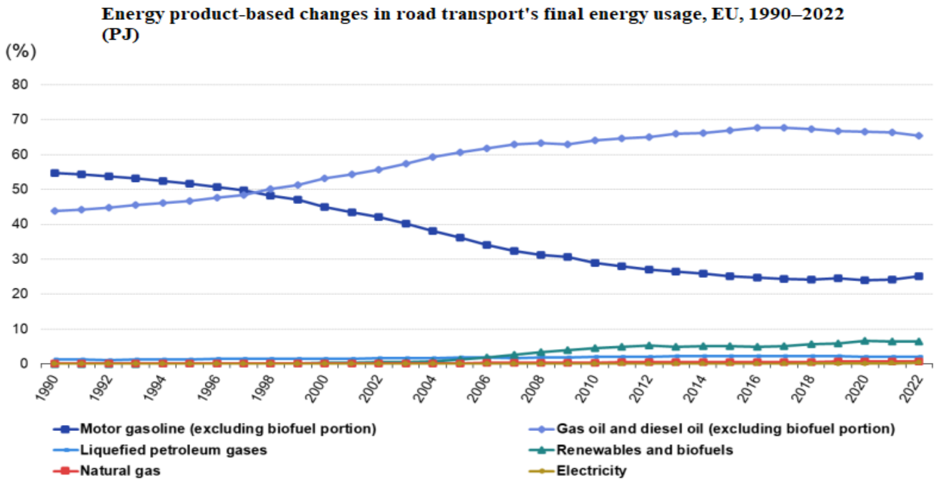

Figure 1. Energy product-based changes in road transport's final energy usage, EU, 1990–2022 (PJ)
(Karayolu taşımacılığında nihai enerji kullanımındaki enerji ürününe dayalı değişimler, AB, 1990–2022 (PJ)) [4]

These statistics clearly demonstrate the urgent need to accelerate the transition toward electric vehicles as a means to minimize environmental effects and dependence on fossil fuels. However, the benefits of electrification can only be fully realized through the implementation of intelligent energy management systems. As electricity becomes a more central energy source in transport, optimizing its use through AI-based strategies is essential—not only to ensure energy efficiency and cost-effectiveness, but also to support the stability of the electricity grid. In this context, the development and evaluation of advanced energy management solutions for electric vehicles becomes a critical step toward achieving sustainable, resilient, and future-ready transportation systems.

Recent studies have underscored the increasing significance of intelligent energy management strategies for electric vehicles, particularly with the integration of artificial intelligence. Lin et al. [5] emphasize the advantages of hybrid energy storage systems—such as combinations of batteries and supercapacitors—in addressing key challenges like vehicle autonomy, battery degradation, and performance optimization. In broader energy networks, Shakeel and Malik [6] explore the application of artificial intelligence in energy microgrids, demonstrating its role in improving energy production and demand management when electric vehicles are integrated into distributed systems. Energy management optimization with the use of reinforced learning and machine learning, as discussed by Pardhasaradhi and Shilaja [7], offers potential for real-time control, operational cost reduction, and enhanced system responsiveness. Similarly, Badran and Toha [8] highlights artificial intelligence in battery management systems for monitoring, cell balancing, and state estimation—critical functions for maintaining battery health and extending lifespan.

Additional advancements have expanded the scope of artificial intelligence across other critical areas of energy management in electric vehicles. Ghalkhani and Habibi [9] investigate its impact on thermal regulation and lithium-ion battery performance, while other studies highlight the role of edge computing in enabling faster, vehicle-level decision-making. Research has also addressed intelligent regenerative braking and the use of harvesting energy mechanically in traffic settings. The transition toward autonomous, connected and shared vehicles has further accelerated the adoption of artificial intelligence in mobility systems. Deep learning, artificial neural networks, and reinforcement learning have been effectively applied in microgrids to optimize energy dispatch and integrate renewable sources. Moreover, genetic optimization algorithms have been developed to manage energy storage in residential solar-powered systems, minimizing costs and increasing self-consumption. Integrated models for forecasting photovoltaic energy and EV charging platforms have also been proposed, aiming to support carbon neutrality and sustainable energy transitions [9].

Given the complexity and multi-dimensional nature of energy management in electric vehicles, evaluating and prioritizing AI-based strategies requires a structured and comprehensive approach. These strategies often involve trade-offs between technical performance, economic feasibility, environmental impact, and integration challenges, making simple decision rules insufficient. In this context, multi-criteria decision-making (MCDM) methods have proven to be highly effective, particularly when used in combination with fuzzy set theory to deal with ambiguity and subjectivity in expert evaluations. The integration of fuzzy logic allows for more realistic modeling of human judgment, which is especially valuable in complex engineering and energy systems. For instance, Alrifaie et al. [10] employed a hybrid Fuzzy Analytical Hierarchical Process and Multi-Attribute Decision-Making approach to support user-centric electric vehicle charging station selection. Similarly, Ghoushchi et al. [11] applied an integrated MCDM model to improve effectiveness in networked self-driving vehicles by incorporating artificial intelligence and IoT-based criteria. Stecyk and Miciuła [12] utilized fuzzy AHP and TOPSIS to evaluate collaborative AI-based platforms for energy optimization, while Imran et al. [13] leveraged fuzzy decision-making techniques to formulate strategies aimed at maximizing electric vehicle utility.

Despite growing interest in electric vehicle technologies and energy optimization, a notable gap exists in the literature concerning the comprehensive identification and evaluation of AI-based energy management strategies specifically for electric vehicles. Most existing studies have focused on isolated aspects, such as selecting optimal charging stations, enhancing the efficiency of autonomous or connected vehicles, or reviewing general energy management systems, without providing an in-depth prioritization of AI-driven strategies. Furthermore, the integration of SWARA-weighted MULTIMOORA methods has not been explored within the electric vehicle industry, particularly in the context of evaluating complex, AI-enabled decision alternatives. This study fills that methodological and thematic gap by introducing a novel framework that combines these decision-making tools with Pythagorean Fuzzy Sets, enabling more accurate and flexible modeling of expert judgment under uncertainty. This integrated approach offers a significant advancement in supporting strategic decision-making for intelligent, sustainable energy management in electric vehicles.

This study aims to bridge the current research gap by establishing a broad evaluation framework for AI-based energy management strategies in electric vehicles. Specifically, the study defines key evaluation criteria and introduces a structured multi-criteria decision-making approach by integrating the Stepwise Weight Assessment Ratio Analysis (SWARA) and Multi-Objective Optimization by Ratio Analysis plus Full Multiplicative Form (MULTIMOORA) methods within a Pythagorean Fuzzy set environment. This integrated framework enables a more robust and uncertainty-aware assessment of AI-driven energy strategies. The primary contributions of this research are summarized as follows:

- Conducting a thorough expert consultation and literature review to identify and define the main AI-based energy management strategies relevant to electric vehicles.
- Employing the SWARA method ascertain the proportional significance of evaluation criteria based on expert judgment.
- Implementing the Pythagorean Fuzzy MULTIMOORA method to rank and prioritize the identified strategies under conditions of uncertainty.
- Performing a sensitivity analysis by systematically altering the weights derived from the SWARA method and recalculating the Ratio System (RS) scores. A total of 21 distinct scenarios are examined to test the robustness of the results.

The findings of this study offer valuable guidance for policy makers and professionals in computer engineering and electrical and electronics fields. For policy makers, the prioritization of AI-based energy management strategies provides a data-driven foundation for shaping supportive policies, investment plans, and infrastructure development aimed at accelerating the transition to sustainable electric mobility. Meanwhile, professionals and researchers in technical fields can benefit from the study's insights to guide the design, development, and implementation of advanced AI algorithms, battery systems, and smart charging technologies—ultimately contributing to more efficient, reliable, and intelligent electric vehicle ecosystems.

2. METHODOLOGY (YÖNTEM)

The evaluation of AI-based energy management strategies for electric vehicles involves multiple, often conflicting factors like cost, flexibility, and energy efficiency, and technological integration. These factors require a multi-criteria decision-making (MCDM) approach to ensure a balanced and systematic assessment. In this research, an integrated methodology combining the SWARA and Pythagorean Fuzzy MULTIMOORA methods is employed to address the complexity and uncertainty inherent in strategic evaluations. The SWARA method is utilized to specify the relative importance of evaluation criteria based on expert judgments. Its strength lies in its simplicity, efficiency, and reduced number of pairwise comparisons, making it especially suitable for expert-driven weighting processes. On the other hand, the MULTIMOORA method, known for its robustness and stability, offers a comprehensive evaluation framework by incorporating three distinct models—Ratio System, Reference Point, and Full Multiplicative Form—to ensure consistency and reliability in ranking alternatives. By embedding these methods in a Pythagorean fuzzy environment, the approach effectively captures the ambiguity and vagueness present in human assessments, thus enhancing decision quality. For this study, SWARA and Pythagorean Fuzzy MULTIMOORA were selected because of their capacity to combine mathematical precision with expert knowledge, offering a flexible and reliable framework for ranking AI-based tactics in the electric vehicle industry.

There are three primary phases to the methodology used in this study. In the first stage, a comprehensive set of evaluation criteria and AI-based energy management strategies for electric vehicles is identified through an extensive literature review and expert consultation. These components are then organized into a hierarchical decision framework. In the second stage, a hybrid multi-criteria decision-making (MCDM) approach is applied. The Stepwise Weight Assessment Ratio Analysis (SWARA) method is used to determine the relative importance (weights) of each criterion based on expert evaluations. These weights are then utilized in the single-valued Pythagorean Fuzzy MULTIMOORA method, which evaluates and ranks the identified strategies by incorporating the Ratio System, Reference Point, and Full Multiplicative Form models to ensure a robust and comprehensive prioritization. In the third stage, a sensitivity analysis is conducted to test the robustness of the model. This is achieved by systematically altering the criterion weights derived from the SWARA method and recalculating the Ratio System scores across 21 distinct scenarios. The results highlight the ranking stability of top-performing strategies and provide insight into how changes in evaluation perspectives affect the overall decision. The schematic figure shown in Figure 2 depicts the specific procedures and integration of the suggested methodology.

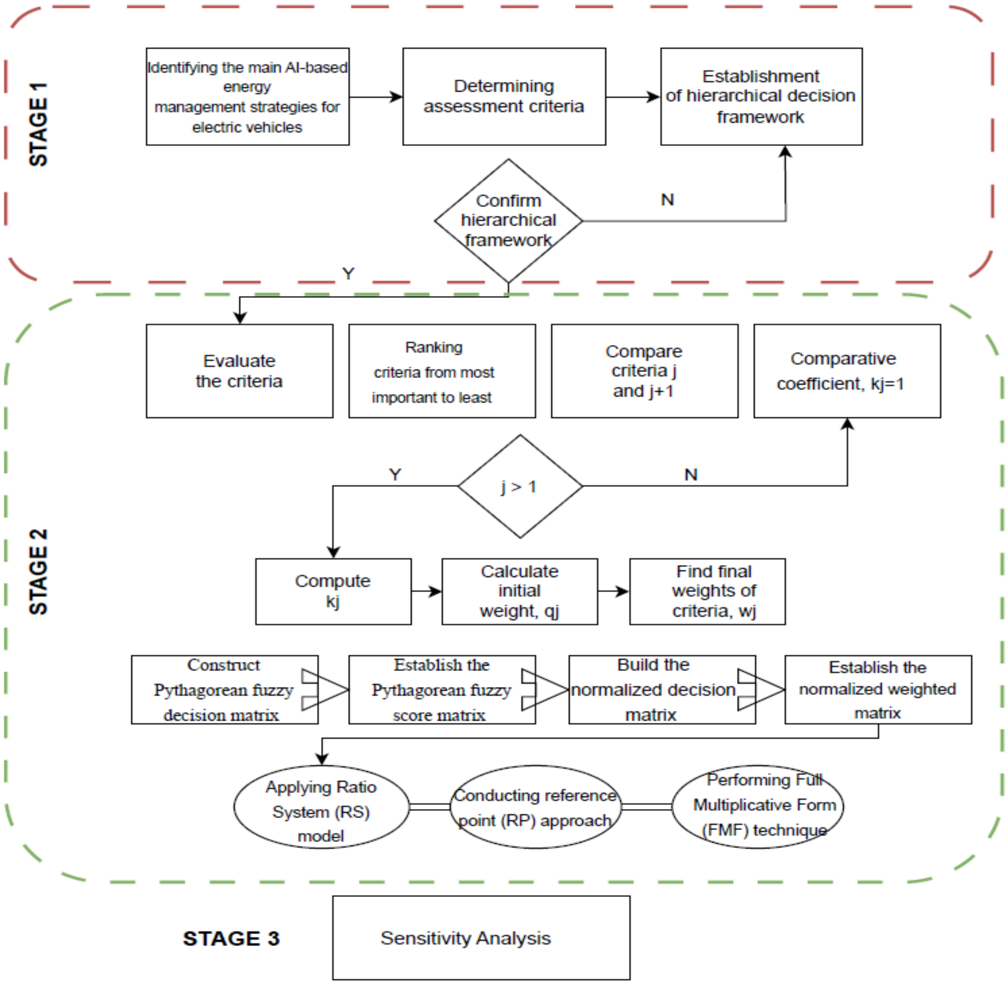

Figure 2. Schematic diagram of methodology (Yöntemin şematik gösterimi)

2.1. Pythagorean Fuzzy Sets (Pisagor Bulanık Kümeler)

Decision-makers evaluating energy management strategies face various uncertainties and subjective judgments, making the analysis of such problems more complex. To handle uncertain information and derive specific outcomes, Zadeh [14] introduced fuzzy set theory and linguistic variables. Recent studies in the literature have expanded on these concepts by incorporating extended fuzzy sets, such as Pythagorean fuzzy sets and intuitionistic fuzzy sets, to more accurately reflect the ambiguity in decision-makers' perspective.

Developed by Atanassov, intuitionistic fuzzy sets (IFSs) incorporate membership, non-membership, and hesitation degrees, with the constraint that degrees of membership and non-membership added together cannot be greater than one. However, since IFSs sometimes fail to adequately model complex uncertainty in practical applications, generalized fuzzy sets such as Pythagorean fuzzy sets (PFSs) have been introduced [15]. The total of the membership and non-membership degrees in PFSs may be greater than one, but the sum of their squares cannot. A geometric comparison between the Pythagorean fuzzy set space and the intuitionistic fuzzy set space reveals that the latter has a wider coverage. As a result, Pythagorean fuzzy sets are more effective in representing uncertainty and imprecision than intuitionistic fuzzy sets.

Definition 1: Let x be an element of the universal set X. A Pythagorean fuzzy set $\tilde{P}$ in X is defined as follows [15]:

$$\tilde{P} = \{\langle x, P(\mu_P(x), v_P(x))\rangle | x \in X\} \qquad (1)$$

where $\mu_P(x)$ ϵ [0,1] represents the membership degree, and $v_P(x)$ ϵ [0,1] denotes the non-membership degree. These membership degrees must satisfy the following condition, given in Equation (2):

$$0 \leq (\mu_P(x))^2 + (v_P(x))^2 \leq 1. \qquad (2)$$

The hesitation degree of a Pythagorean fuzzy number in $\tilde{P}$ is identified in Equation (3) as follows:

$$\pi_P(x) = \sqrt{1-\left(\mu_P(x)\right)^2-\left(v_P(x)\right)^2} \quad (3)$$

Definition 2: Let $\tilde{P}_1 = P\left(\mu_{P_1}, v_{P_1}\right)$ and $\tilde{P}_2 = P\left(\mu_{P_2}, v_{P_2}\right)$ be two Pythagorean fuzzy numbers, and let λ be a positive number. The fundamental operations in Pythagorean fuzzy sets are shown below:

$$\tilde{P}_1 \otimes \tilde{P}_2 = \mathrm{P}\left(\mu_{P_1}\mu_{P_2}, \sqrt{\left(v_{P_1}\right)^2+\left(v_{P_2}\right)^2-\left(v_{P_1}\right)^2\left(v_{P_2}\right)^2}\right) \quad (4)$$

$$\lambda\tilde{P}_1 = \left(\sqrt{1-(1-\left(\mu_{P_1}\right)^2)^{\lambda}}, (v_{P_1})^{\lambda}\right), \quad \lambda > 0, \quad (5)$$

$$\left(\tilde{P}_1\right)^{\lambda} = \left((\mu_{P_1})^{\lambda}, \sqrt{1-(1-\left(v_{P_1}\right)^2)^{\lambda}}\right), \quad \lambda > 0. \quad (6)$$

$$\tilde{P}_1 \ominus \tilde{P}_2 = \left(\sqrt{\frac{\mu_1^2-\mu_2^2}{1-\mu_2^2}}, \frac{v_1}{v_2}\right) \text{ if } \mu_{P_1} \geq \mu_{P_2}, v_{P_1} \leq \min\left\{v_{P_2}, \frac{v_{P_2}\pi_{P_1}}{\pi_{P_2}}\right\} \quad (7)$$

$$\frac{\tilde{P}_1}{\tilde{P}_2} = \left(\frac{\mu_1}{\mu_2}, \sqrt{\frac{v_1^2-v_2^2}{1-v_2^2}}\right) \text{ if } \mu_{P_1} \leq \min\left\{\mu_{P_2}, \frac{\mu_{P_2}\pi_{P_1}}{\pi_{P_2}}\right\}, v_{P_1} \geq v_{P_2} \quad (8)$$

Definition 3: Let $\tilde{P}_i = P(\mu_i, v_i)$, $i = (1,2,\ldots,n)$ be a group of Pythagorean fuzzy sets. The Pythagorean fuzzy weighted averaging (PFWA) formula, given in Equation (9), is used to aggregate this set.

$$\text{PFWA}\left(\tilde{P}_1, \tilde{P}_2, \ldots, \tilde{P}_n\right) = \left(\left(1-\prod_{i=1}^{n}(1-\mu_i^2)^{w_i}\right)^{1/2}, \left(\prod_{i=1}^{n}(v_i)^{w_i}\right)\right) \quad (9)$$

where $w_i = (w_1, w_2, \ldots, w_n)$ be the weight vector of $\tilde{P}_i$, $i = (1,2,\ldots,n)$ with $w_i \in [0, 1]$ and $\sum_{i=1}^{n} w_i = 1$.

Definition 4: Let $\tilde{P}_1 = P\left(\mu_{P_1}, v_{P_1}\right)$ and $\tilde{P}_2 = P\left(\mu_{P_2}, v_{P_2}\right)$ be two Pythagorean fuzzy numbers. To compare and rank these two numbers, score functions are used. The formula for the score function is shown in Equation (10):

$$s(\tilde{P}_1) = \left(\mu_{P_1}\right)^2 - \left(v_{P_1}\right)^2. \quad (10)$$

2.2. SWARA Method (SWARA Yöntemi)

The Stepwise Weight Assessment Ratio Analysis (SWARA) method was introduced by Kersuliene et al. [16] to determine subjective criterion weights. One key advantage of SWARA is its simplicity, as it involves fewer computational steps and requires a minimal number of pairwise comparisons compared to other weighting techniques like Analytic Hierarchy Process (AHP). Another strength of SWARA lies in its reliance on decision-makers' judgments, where initial prioritization and relative importance are established based on expert opinions. The following are the steps involved in the SWARA method's process:

Step 1: Identify alternatives $(i = 1,2,\ldots,m)$ and criteria $(j = 1,2,\ldots,n)$.

Step 2: Experts' preferences are used to rank the criteria from most to least important.

Step 3: Criteria are compared with each other to determine their relative importance levels. The (j)th criterion is compared to the (j-1)th criterion, and a value (S_j) is assigned within the 0-1 range.

Step 4: Compute the proportional significance of every criterion (S_j) by comparing it with the previous criterion, and calculate the comparative coefficient (k_j) using Equation (11).

$$k_j = \begin{cases} 1, & j = 1 \\ S_j + 1, & j > 1 \end{cases} \quad (11)$$

Step 5: The initial weight for every factors (q_j) is determined utilizing the Equation (12).

$$q_j = \begin{cases} 1, & j = 1 \\ \frac{q_{j-1}}{k_j}, & j > 1 \end{cases} \quad (12)$$

Step 6: Final criterion weight (ω_i) is computed with Equation (13).

$$\omega_i = \frac{q_j}{\sum_{j=1}^{n} q_j} \quad (13)$$

2.3. Pythagorean Fuzzy MULTIMOORA (Pisagor Bulanık MULTIMOORA)

In this study, the MULTIMOORA (Multi-Objective Optimization by Ratio Analysis plus Full Multiplicative Form) method is employed to evaluate and rank AI-based energy management strategies for electric vehicles. Initially, Brauers and Zavadskas [17] introduced as an enhancement of the MOORA method, MULTIMOORA combines three distinct approaches—Ratio System (RS), Reference Point (RP), and Full Multiplicative Form (FMF)—to improve the robustness and accuracy of multi-criteria decision-making (MCDM). This integrated framework is recognized for its ability to address conflicting objectives, handle a wide range of criteria, and provide consistent evaluations even in complex decision environments. To further strengthen its capacity to cope with vagueness and imprecise expert judgments often encountered in real-world evaluations, the method is extended using Pythagorean Fuzzy Sets, resulting in the Pythagorean Fuzzy MULTIMOORA (PF-MULTIMOORA) approach. This extension enhances the model's ability to represent uncertainty more flexibly, thereby offering a more reliable and realistic framework for prioritizing energy management strategies in electric vehicle systems. The steps of PF-MULTIMOORA are as follows:

Step 1: Construct Pythagorean fuzzy decision matrix $D = \left(C_j(x_i)\right)_{m\times n}$ using Equation (14), where $C_j(j = 1,2,\dots,n)$ and $x_i(i = 1,2,\dots,m)$ be the criteria and alternatives respectively.

$$D = \left(C_j(x_i)\right)_{m\times n} = \begin{array}{c c} & \begin{array}{ccc} C_1 & \cdots & C_n \end{array} \\ \begin{array}{c} x_1 \\ \vdots \\ x_m \end{array} & \begin{bmatrix} P_{11} & \cdots & P_{1n} \\ \vdots & \ddots & \vdots \\ P_{m1} & \cdots & P_{mn} \end{bmatrix} \end{array} \quad (14)$$

Step 2: Combine the Pythagorean fuzzy decision matrix by applying the Pythagorean Fuzzy Weighted Averaging (PFWA) method, as outlined in Equation (9).

Step 3: Construct the Pythagorean fuzzy score matrix S = $(X_{ij})_{m\times n}$ using Equation (10).

Step 4: Build the normalized decision matrix N = $(n_{ij})_{m\times n}$, where the normalization is performed using Equation (15). In this step, X_{ij}^+ and X_{ij}^- represent the maximum and minimum values of each criterion across all alternatives, respectively.

$$n_{ij} = \begin{cases} \dfrac{X_{ij}-X_{ij}^-}{X_{ij}^+-X_{ij}^-} & if\ j \in C_b, \\ \dfrac{X_{ij}^+-X_{ij}}{X_{ij}^+-X_{ij}^-} & if j \in C_c \end{cases} \quad (15)$$

where C_b and C_c show the benefit criteria and cost criteria.

Step 5: Establish the normalized weighted matrix using Equation (16):

$$n_{ij}^{\cdot} = n_{ij} \times \omega_j \quad (16)$$

Step 6: Determine the ranking of the alternatives using the Ratio System (RS) model. In the MULTIMOORA method, the RS model is applied to establish the relative priority of each alternative and identify the most appropriate option. The scores for the alternatives within the ratio system framework are computed using Equation (17):

$$y_i = y_i^+ - y_i^- = \sum_{j=1}^{g} \dot{n}_{ij} - \sum_{j=g+1}^{n} \dot{n}_{ij} \quad (17)$$

In this case, y_i is the normalized value of the *i-th* choice across all criteria, g is the number of criteria to be maximized, and n is the number of criteria to be minimized. The optimal option is the one with the highest rating after the y_i values are arranged in descending order.

Step 7: Assess the alternatives using the reference point (RP) approach. The Tchebycheff Min-Max metric is computed using Equation (18).

$$D_i = \min_{(i)} \left\{ \max_{j} \left| n_j - \dot{n}_{ij} \right| \right\} \quad (18)$$

The reference point (n_j) for each criterion is chosen from the greatest values of the alternatives in the case of maximizing and the lowest values in the case of minimization. For every option, the greatest value (D_i) is computed. Next, the options are arranged in ascending order of preference.

Step 8: Determine the ranking of the alternatives by applying the Full Multiplicative Form (FMF) technique. The overall utility score for each alternative is calculated using Equation (19):

$$U_i = \prod_{j=1}^{g} \dot{n}_{ij} \ / \ \prod_{j=g+1}^{n} \dot{n}_{ij} \quad (19)$$

In this context, the benefit criteria are indexed from j = 1 to g, while the cost criteria are represented from j = g + 1 to n.

Step 9: Rank the alternatives and compare the outcomes derived from the Reference Point (RP) approach, Ratio System (RS) model, and the Full Multiplicative Form (FMF) technique.

3. CASE STUDY (VAKA ÇALIŞMASI)

As electric vehicles become more widespread, efficient energy management is essential for maximizing performance and sustainability. AI-based strategies offer innovative solutions by enabling smart, adaptive control of energy use. However, due to the complexity of these approaches, a structured evaluation is needed. This study is important as it provides a comprehensive assessment of key AI-driven energy management strategies, helping stakeholders identify the most effective and practical solutions for advancing intelligent and sustainable mobility.

This study aims to evaluate and prioritize AI-based energy management strategies for electric vehicles using multi-criteria decision-making approaches. By assessing their energy efficiency, economic viability, environmental impact, and technological adaptability, the research offers a structured framework to guide stakeholders in identifying and adopting the most effective strategies. The primary AI-based energy management strategies are determined through a comprehensive literature review and expert consultations as follows:

Predictive Energy Optimization (A1): AI-driven predictive models analyze real-time traffic, weather conditions, and historical driving patterns to optimize energy consumption [7]. Machine learning algorithms anticipate energy needs and dynamically adjust power distribution between the battery, motor, and auxiliary systems, ensuring extended range and reduced energy waste.

Smart Battery Management Systems (A2): AI enhances battery performance by continuously monitoring charge levels, temperature, and health indicators. It predicts battery degradation, optimizes charging cycles, and balances cell voltages to extend battery lifespan while ensuring efficiency and safety [8]. Advanced deep learning techniques help prevent overcharging and overheating issues.

AI-Optimized Route and Driving Assistance (A3): AI integrates GPS, traffic data, and energy consumption models to suggest the most energy-efficient routes. By considering road gradients, congestion, and charging station availability, AI-powered navigation helps EVs minimize energy use [5]. Additionally, AI-based driving assistants adjust acceleration and braking patterns to improve efficiency.

AI-Powered Regenerative Braking Optimization (A4): Regenerative braking systems use AI to maximize energy recovery by adapting braking intensity based on road conditions and driver behavior [7]. AI optimally distributes the recovered energy back to the battery, reducing reliance on external charging and improving overall efficiency.

AI-Enabled Smart Charging and Grid Integration (A5): AI synchronizes EV charging with smart grids by analyzing electricity demand, price fluctuations, and grid stability. It schedules charging during low-demand hours to reduce costs and enables Vehicle-to-Grid (V2G) technology, where EVs improve grid resilience by returning power to the grid during periods of peak demand [9].

AI-Driven Thermal Management (A6): AI regulates the vehicle's thermal systems, optimizing battery cooling and cabin climate control to minimize unnecessary energy usage [18]. By predicting external temperature changes and driver preferences, AI efficiently distributes energy between the ventilation, heating and air conditioning (HVAC) system and other power needs, increasing overall vehicle efficiency.

The evaluation of AI-based energy management strategies for electric vehicles requires a comprehensive and multidimensional approach, as these strategies directly affect the performance, sustainability, and practicality of electric vehicles. To ensure a thorough assessment, seven critical criteria are identified, capturing the most essential aspects of energy management in EVs. These criteria encompass technical, economic, environmental, and regulatory dimensions, enabling decision-makers to objectively compare and prioritize different AI-based strategies. The selected criteria and their detailed explanations are provided below:

Energy Efficiency (C1): This criterion assesses how well the AI-based strategy optimizes energy consumption to extend the driving range. It considers intelligent power distribution, regenerative braking efficiency, and predictive energy management to minimize waste and improve overall vehicle performance.

Economic Feasibility (C2): This evaluates the financial viability of the strategy, including implementation costs, operational expenses, and potential long-term savings. AI-driven solutions that reduce electricity consumption, optimize charging costs, and provide a favorable return on investment rank higher in this category.

Time Efficiency & Performance (C3): This aspect considers how AI strategies impact charging time, route optimization, and overall operational efficiency. Strategies that reduce charging duration, minimize energy loss during transmission, and optimize real-time power management are rated more favorably.

Adaptability & Scalability (C4): This measures the flexibility of AI strategies in handling different driving environments, vehicle models, and traffic conditions. AI systems that can be easily integrated into diverse EV fleets, adjust to dynamic energy demands, and scale with technological advancements receive a higher score.

Environmental Sustainability (C5): This criterion evaluates the extent to which the AI strategy reduces greenhouse gas emissions, promotes renewable energy integration, and minimizes environmental impact. AI solutions that enable smart grid interactions, prioritize clean energy sources, and support eco-friendly driving behavior perform better in this category.

Technological Integration (C6): This assesses the compatibility of AI-based energy management with existing EV infrastructures, including smart charging systems, IoT devices, and cloud-based platforms. Solutions that ensure seamless integration with vehicle control systems, maintain high reliability, and minimize disruptions are prioritized.

Regulatory Compliance (C7): This criterion examines whether the AI strategy aligns with government regulations, safety standards, and energy policies. Strategies that adhere to evolving legal frameworks, data privacy laws, and electric mobility regulations while ensuring cybersecurity are considered more effective.

In this study, a hierarchical framework is developed to clearly structure the decision-making process for evaluating AI-based energy management strategies for electric vehicles. At the top level of the hierarchy lies the main objective—to prioritize and evaluate the most effective AI-driven strategies in the context of electric vehicle energy management. The second level comprises the evaluation criteria, which reflect key factors such as energy efficiency, economic feasibility, technological integration, and environmental sustainability. At the final level, the specific AI-based strategies identified through literature review and expert input are positioned as the alternatives to be assessed. This hierarchical structure provides a transparent and logical foundation for applying the integrated SWARA and Pythagorean Fuzzy MULTIMOORA methodology. The complete hierarchical decision model is visually represented in Figure 3.

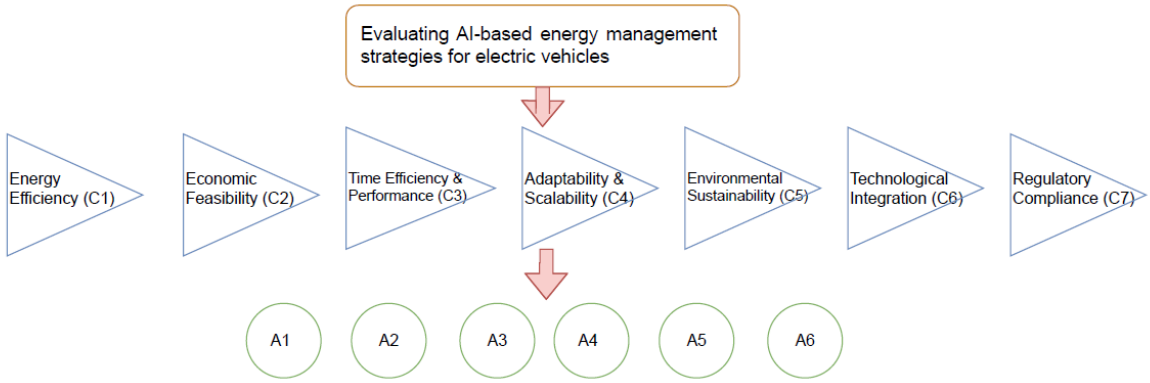

Figure 3. Hierarchical decision model of this study (Çalışmanın hiyerarşi karar modeli)

3.1. Application (Uygulama)

This study applies SWARA-weighted MULTIMOORA methodology under Pythagorean fuzzy environment to evaluate artificial intelligence-driven energy optimization strategies for electric vehicles. By reviewing the literature and consulting with academic and industry decision-makers, evaluation criteria and strategies are established.

In the initial stage of the methodology, the expert team evaluated and compared the criteria to determine their relative importance. In the third step of the SWARA method, each criterion is compared with the preceding one to determine its relative importance. The (S_j) values in Table 1 reflect the comparison of criterion j with criterion (j–1). For example, Technological Integration (C6) is compared with Energy Efficiency (C1), and Regulatory Compliance (C7) is evaluated against Environmental Sustainability (C5). This sequential structure is consistent with the standard SWARA procedure, where each criterion is assessed relative to the one ranked just before it. Subsequently, the comparative coefficient (k_j) was calculated using Equation (11), followed by the computation of the initial weight for each criterion (q_j) using Equation (12). Finally, the final weights of the criteria (ω_i) were obtained using Equation (13). The results of the SWARA approach are presented in Table 1.

Table 1. SWARA Method Results (SWARA yöntemi sonuçları)

Criteria	S_j	K_j	q_j	w_j
Energy Efficiency (C1)	-	1.000	1.000	0.379
Technological Integration (C6)	0.650	1.650	0.606	0.229
Economic Feasibility (C2)	0.450	1.450	0.418	0.158
Adaptability & Scalability (C4)	0.700	1.700	0.246	0.093
Time Efficiency & Performance (C3)	0.350	1.350	0.182	0.069
Environmental Sustainability (C5)	0.650	1.650	0.110	0.042
Regulatory Compliance (C7)	0.400	1.400	0.079	0.030

The results of the SWARA method reveal that Energy Efficiency (C1) is the most critical criterion in evaluating AI-based energy management strategies for electric vehicles, holding the highest weight of 0.379. This is followed by Technological Integration (C6) with a weight of 0.229, and Economic Feasibility (C2) with 0.158, reflecting their strong influence on decision-making. Adaptability & Scalability (C4) ranks fourth with 0.093, while Time Efficiency & Performance (C3) holds a moderate importance at 0.069. Environmental Sustainability (C5) and Regulatory Compliance (C7) are considered less significant, with weights of 0.042 and 0.030, respectively. These results indicate a clear emphasis on technical performance and cost-effectiveness over regulatory or environmental aspects in the context of electric vehicle energy strategies.

In the second phase, the single-valued Pythagorean Fuzzy MULTIMOORA method is applied using the criterion weights obtained from the first phase. To implement this approach, a decision matrix is established on the basis of linguistic variables represented by Pythagorean fuzzy numbers, as outlined in Table 2.

Table 2. Pythagorean fuzzy number linguistic variables (Pisagor bulanık sayıların dilsel terimleri)

Linguistic term	Corresponding Pythagorean Fuzzy Member (u,v)
Very Low (VL)	(0.15, 0.85)
Low (L)	(0.25, 0.75)
Moderately Low (ML)	(0.35, 0.65)
Medium (M)	(0.50, 0.45)
Moderately High (MH)	(0.65, 0.35)
High (H)	(0.75, 0.25)
Very High (VH)	(0.85, 0.15)

The decision matrix, presented in Table 3, was developed based on evaluations provided by a panel of three experts, comprising one academic and two professionals from the automotive industry. During the evaluation process, the experts reached a consensus through direct discussion, eliminating the need for aggregating differing opinions using operators such as the Pythagorean Fuzzy Weighted Averaging (PFWA). Nevertheless, the PFWA operator is introduced conceptually in Section 2.1 to inform readers and support future studies that may require the integration of diverse expert judgments.

After constructing the Pythagorean fuzzy decision matrix, a Pythagorean fuzzy score matrix was established using Equation (10) to transform fuzzy sets into crisp values. This transformation was carried out by applying a score function that quantifies each Pythagorean fuzzy number into a real number between 0 and 1, thereby enabling numerical comparison between alternatives. The resulting crisp values reflect the relative performance of each strategy under each criterion and are essential for subsequent normalization and aggregation steps.

Table 3. Decision matrix (Karar matrisi)

Alternative/Criteria	Energy Efficiency (C1)	Economic Feasibility (C2)	Time Efficiency & Performance (C3)	Adaptability & Scalability (C4)	Environmental Sustainability (C5)	Technological Integration (C6)	Regulatory Compliance (C7)
Predictive Energy Optimization (A1)	VH	ML	M	H	H	H	H
Smart Battery Management Systems (A2)	VH	L	ML	VH	VH	VH	H
AI-Optimized Route and Driving Assistance (A3)	H	ML	MH	MH	MH	H	MH
AI-Powered Regenerative Braking Optimization (A4)	MH	M	M	M	MH	MH	M
AI-Enabled Smart Charging and Grid Integration (A5)	H	ML	ML	H	VH	H	MH
AI-Driven Thermal Management (A6)	M	ML	H	M	MH	M	ML

Following the transformation of expert evaluations into crisp values using the score function, the normalization process is carried out using Equation (15), followed by the construction of the normalized weighted decision matrix using Equation (16). As part of the normalization step, benefit-type criteria—such as Energy Efficiency (C1), Adaptability & Scalability (C4), Environmental Sustainability (C5), Technological Integration (C6), and Regulatory Compliance (C7)—are normalized by assigning higher scores to better-performing alternatives. Conversely, for cost-type criteria—namely Economic Feasibility (C2) and Time Efficiency & Performance (C3)—lower values are preferred and scored accordingly. This approach ensures that all criteria, regardless of their nature, are brought onto a unified scale between 0 and 1, where 1 represents the most favorable performance and 0 the least. As a result, the normalized decision matrix presented in Table 4 enables a fair and consistent comparison among the alternative strategies prior to applying the MULTIMOORA method. To enhance the robustness and accuracy of the multi-criteria decision-making process, the three distinct components of the MULTIMOORA method—Ratio System (RS), Reference Point (RP), and Full Multiplicative Form (FMF)—are applied independently. This comprehensive approach ensures a more reliable and consistent evaluation of the alternatives.

Table 4. Normalized decision matrix (Normalize karar matrisi)

Alternative/Criteria	Energy Efficiency (C1)	Economic Feasibility (C2)	Time Efficiency & Performance (C3)	Adaptability & Scalability (C4)	Environmental Sustainability (C5)	Technological Integration (C6)	Regulatory Compliance (C7)
Predictive Energy Optimization (A1)	1.00	0.63	0.57	0.69	0.50	0.69	1.00
Smart Battery Management Systems (A2)	1.00	1.00	1.00	1.00	1.00	1.00	1.00

AI-Optimized Route and Driving Assistance (A3)	0.69	0.63	0.25	0.39	0.00	0.69	0.75
AI-Powered Regenerative Braking Optimization (A4)	0.39	0.00	0.57	0.00	0.00	0.39	0.43
AI-Enabled Smart Charging and Grid Integration (A5)	0.69	0.63	1.00	0.75	1.00	0.69	0.75
AI-Driven Thermal Management (A6)	0.00	0.63	0.00	0.00	0.00	0.00	0.00

The RS model is first applied to determine the relative priority of each alternative using Equation (17). Subsequently, the Tchebycheff Min-Max metric is calculated to evaluate the alternatives through the RP approach, as defined by Equation (18). Finally, the overall utility score for each alternative is computed by applying the FMF technique using Equation (19) to establish their final rankings. The results obtained from the Ratio System (RS), Reference Point (RP), and Full Multiplicative Form (FMF) approaches are presented in Table 5. In the RS model, the y_i values are ranked in descending order, where a higher value indicates a more preferable alternative. For the RP approach, the maximum distance value D_i is calculated for each alternative, and the alternatives are ranked in ascending order, with lower values indicating better performance. In the FMF technique, the utility scores U_i are also ranked in descending order, where the highest score reflects the most ideal alternative.

Table 5. The results obtained from the RS, RP, and FMF approaches (RS, RP ve FMF yaklaşımlarından elde edilen sonuçlar)

Alternative	y_i	D_i	U_i
Predictive Energy Optimization (A1)	0.51	0.10	4.68
Smart Battery Management Systems (A2)	0.55	0.12	6.37
AI-Optimized Route and Driving Assistance (A3)	0.36	0.12	4.08
AI-Powered Regenerative Braking Optimization (A4)	0.21	0.23	3.40
AI-Enabled Smart Charging and Grid Integration (A5)	0.39	0.12	3.28
AI-Driven Thermal Management (A6)	-0.10	0.38	0.00

Figure 4 indicates the ranking results of three approaches. Smart Battery Management Systems (A2) consistently rank as the top-performing strategy across all three methods, highlighting its critical role in optimizing energy use and prolonging battery life. Similarly, AI-Driven Thermal Management (A6) ranks lowest in all methods, suggesting it may currently offer less impact or maturity compared to other strategies. AI-Optimized Route and Driving Assistance (A3) and AI-Powered Regenerative Braking Optimization (A4) occupy middle-tier rankings, indicating moderate yet stable performance. Minor variances across methods, such as the relative positions of Predictive Energy Optimization (A1) and AI-Enabled Smart Charging and Grid Integration (A5), suggest that while the overall hierarchy remains stable, method-specific criteria can influence the finer details of strategy prioritization.

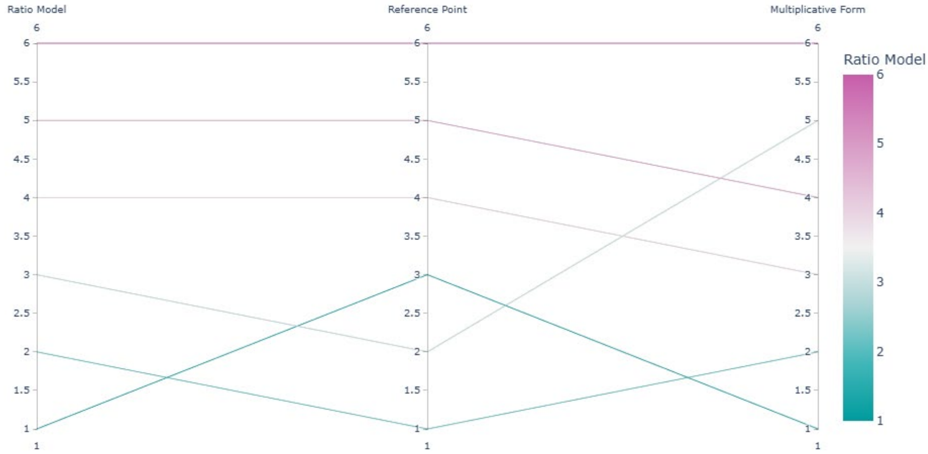

Figure 4. Ranking results of three approaches (Üç yaklaşıma ait sıralama sonuçları)

3.2. Sensitivity Analysis (Duyarlılık Analizi)

Sensitivity analysis is a valuable tool employed to evaluate the reliability of a decision-making framework by observing how fluctuations in input parameters—particularly criteria weights—affect the final rankings of alternatives. In this study, sensitivity analysis is conducted to investigate the impact of changes in the importance levels assigned to evaluation criteria on the prioritization of AI-based energy management strategies for electric vehicles. By systematically interchanging the weights of each criterion, the analysis reveals whether the ranking of strategies remains consistent or is significantly altered. A change in the ranking order following the modification of a criterion's weight indicates that the model is sensitive to that specific parameter, highlighting its influence on the decision outcome. On the other hand, if the rankings remain stable despite weight adjustments, it suggests a robust decision-making model. This process ensures the consistency and credibility of the applied methodology under varying assumptions, reinforcing the dependability of the results in diverse decision environments.

In this research, sensitivity analysis is carried out by modifying the criterion weights obtained through the SWARA method and recalculating the Ratio System (RS) scores using the Pythagorean Fuzzy MULTIMOORA approach. A total of 21 distinct scenarios are analyzed, each involving a pairwise swap of weight values between two criteria. For instance, the notation $y_{i\,1\text{-}2}$ indicates a scenario where the weight of Criterion 1 is exchanged with that of Criterion 2. Figure 5 shows the heatmap of RS model scores (y_i values) for six alternatives (A1–A6) across 21 different sensitivity scenarios, each representing a weight swap between a pair of evaluation criteria. The heatmap highlights how each alternative's performance fluctuates under different weighting conditions. Alternative A2 (Smart Battery Management Systems) consistently scores high across all scenarios, indicating strong robustness and insensitivity to weight variations. In contrast, "AI-Driven Thermal Management (A6)" remains consistently low or negative in all cases, suggesting weak overall performance and possibly unfavorable evaluation under all weighting schemes. Alternatives A1, A3, and A5 show moderate variability, with A1 and A5 reaching relatively high scores in several scenarios, indicating they are sensitive but potentially competitive depending on the criteria emphasis. A4 tends to stay on the lower end but shows some resilience in select scenarios.

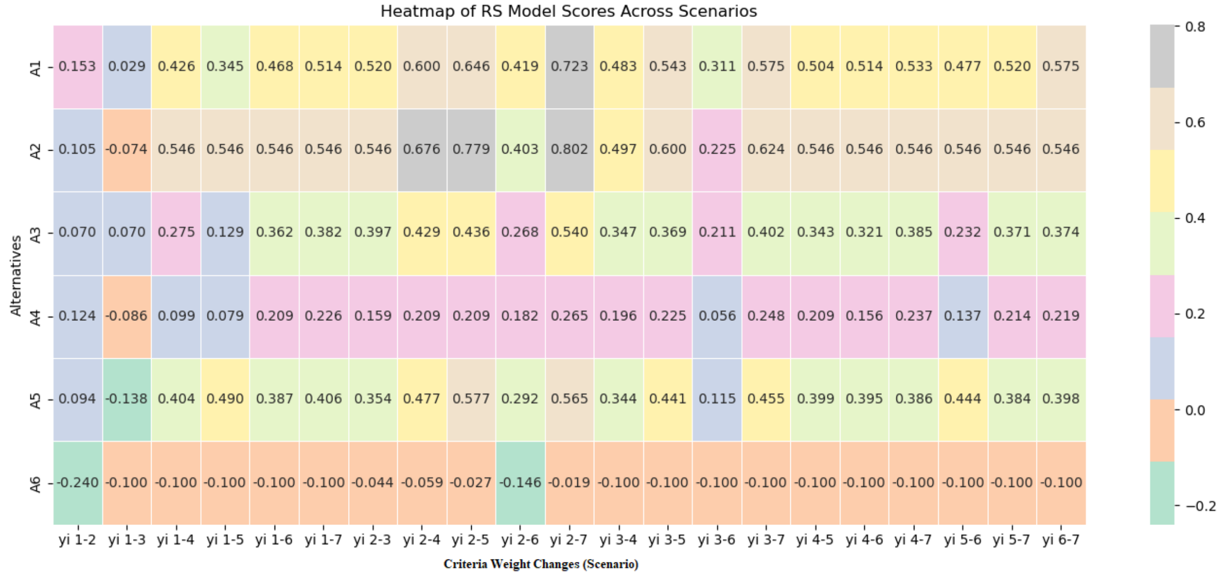

Figure 5. RS Model results across 21 scenarios (RS Modeli sonuçlarının 21 senaryo karşısındaki dağılımı)

Figure 6 shows the ranking results of the alternatives across all 21 sensitivity analysis scenarios, clearly visualizing the dynamic shifts in ranking positions and highlighting the stability of top-performing strategies under different evaluation perspectives. As observed in the data, Alternatives A1 and A2 consistently outperform others, frequently securing the 1st and 2nd ranks in most scenarios, indicating their robustness and reliability under changing priority conditions. In contrast, Alternative A6 remains fixed at the 6th position across all scenarios, suggesting its relatively poor performance regardless of weight variation. Alternatives A3, A4, and A5 exhibit more variability, occasionally reaching middle-tier rankings, but never achieving top ranks consistently. This variability indicates that their effectiveness is more sensitive to the weight distribution of the criteria.

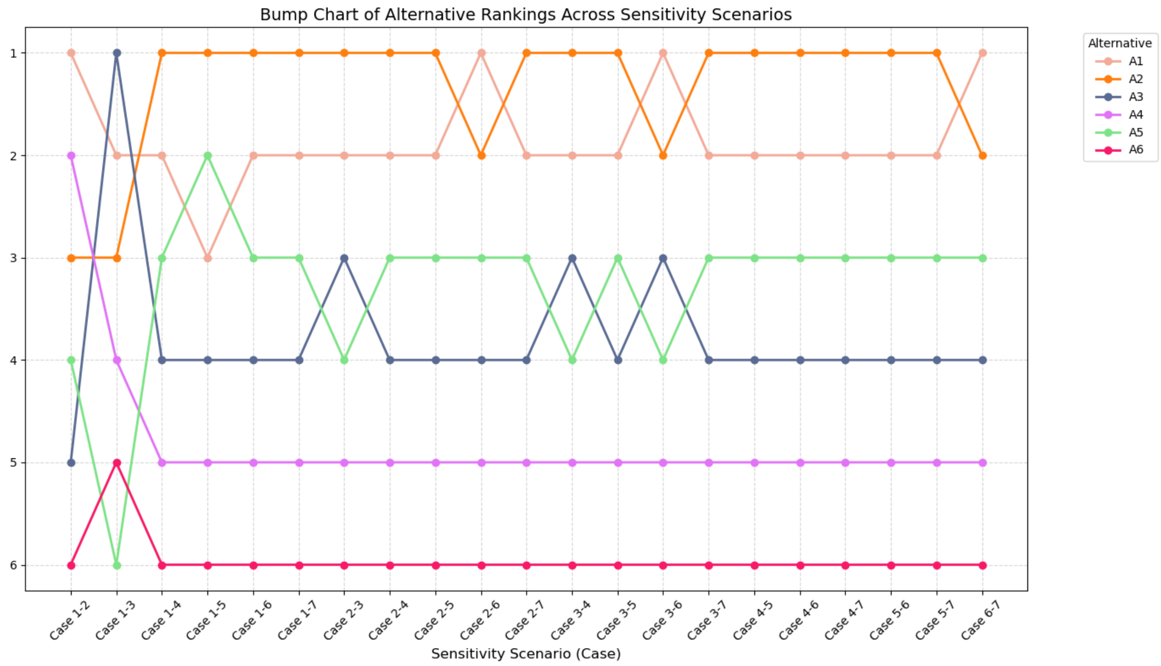

Figure 6. Ranking results of the alternatives across all 21 scenarios (Alternatiflerin 21 senaryo boyunca sıralama sonuçları)

3.3. Comparative Analysis (Karşılaştırma Analizi)

To validate the robustness and reliability of the proposed SWARA–Pythagorean Fuzzy MULTIMOORA framework, a comparative analysis was performed using the Pythagorean Fuzzy TOPSIS (PF-TOPSIS) method. Such comparative evaluations are essential in multi-criteria decision-making (MCDM) studies, as they provide a benchmark for assessing the consistency of results and the practical applicability of alternative approaches under different decision environments.

The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), originally proposed by Hwang and Yoon [19], is a widely adopted MCDM method that selects the optimal alternative based on its geometric proximity to a positive ideal solution (PIS) and its distance from a negative ideal solution (NIS). To effectively manage uncertainty in decision-making, this method has been extended into the Pythagorean fuzzy domain, resulting in the Pythagorean Fuzzy TOPSIS (PF-TOPSIS) approach.

This method was selected for comparison due to its popularity in the literature, ease of interpretation, and ability to offer a reliable ranking mechanism in fuzzy environments. On the basis of definition above, the procedural steps of the PF-TOPSIS method are outlined below:

Step 10: Calculate Pythagorean fuzzy positive ideal solution (PIS) and negative ideal solution (NIS) using Equations (20) and (21):

$$x^+ = \left\{\max_i \langle s((x_i))\rangle \middle| j = 1,2,\cdots,n\right\} = \{\langle P(u_1^+, v_1^+)\rangle, \langle P(u_2^+, v_2^+)\rangle, \cdots, \langle P(u_n^+, v_n^+)\rangle\}, \quad (20)$$

$$x^- = \left\{\min_i \langle s((x_i))\rangle \middle| j = 1,2,\cdots,n\right\} = \{\langle P(u_1^-, v_1^-)\rangle, \langle P(u_2^-, v_2^-)\rangle, \cdots, \langle P(u_n^-, v_n^-)\rangle\}. \quad (21)$$

Step 11: Compute distances from Pythagorean fuzzy PIS and NIS using Equations (22) and (23):

$$D(x_i, x^+) = \sum_{j=1}^{n} w_j d\left(C_j(x_i), C_j(x^+)\right) = \frac{1}{2}\sum_{j=1}^{n} w_j \left(\left|(\mu_{ij})^2 - (\mu_j^+)^2\right| + \left|(v_{ij})^2 - (v_j^+)^2\right| + \left|(\pi_{ij})^2 - (\pi_j^+)^2\right|\right), i = 1,2,\cdots,m, \quad (22)$$

$$D(x_i, x^-) = \sum_{j=1}^{n} w_j d\left(C_j(x_i), C_j(x^-)\right) = \frac{1}{2}\sum_{j=1}^{n} w_j \left(\left|(\mu_{ij})^2 - (\mu_j^-)^2\right| + \left|(v_{ij})^2 - (v_j^-)^2\right| + \left|(\pi_{ij})^2 - (\pi_j^-)^2\right|\right), i = 1,2,\cdots,m. \quad (23)$$

Step 12: Determine the revised closeness $\xi(x_i)$ of the alternative x_i using Eq. (24):

$$\xi(x_i) = \frac{D(x_i, x^-)}{D_{max}(x_i, x^-)} - \frac{D(x_i, x^+)}{D_{min}(x_i, x^+)} \quad (24)$$

Step 13: Determine the best ranking order of alternatives in which the best alternative is the one that has the largest revised closeness $\xi(x_i)$.

The implementation of the PF-TOPSIS method begins with the calculation of the Pythagorean Fuzzy Positive Ideal Solution (PIS) and Negative Ideal Solution (NIS) using Equations (20) and (21). These reference points represent the best and worst possible performance across all criteria, respectively. The results of these calculations are presented as follows:

x^+ = {P(0.85, 0.15), P(0.50, 0.45), P(0.75, 0.25), P(0.85, 0.15), P(0.85, 0.15), P(0.85, 0.15), P(0.75, 0.25)}

x^- = {P(0.50, 0.45), P(0.25, 0.75), P(0.35, 0.65), P(0.50, 0.45), P(0.65, 0.35), P(0.50, 0.45), P(0.35, 0.65)}.

Next, the distances of each alternative from the Pythagorean Fuzzy PIS and NIS are determined using Equations (22) and (23). Based on these distances, the revised closeness coefficient $\xi(x_i)$ for each alternative is computed using Equation (24). This coefficient indicates how close each alternative is to the ideal solution, with higher values signifying better performance. Table 6 provides a comparison between the PF-TOPSIS method and the proposed SWARA–Pythagorean Fuzzy MULTIMOORA framework. It includes the calculated distances from the PIS and NIS, as well as the resulting closeness coefficients and rankings for each alternative.

Table 6. Comparative results between the PF-TOPSIS method and the proposed approach (PF-TOPSIS yöntemi ile önerilen yaklaşım arasındaki karşılaştırmalı sonuçlar)

Alternative	PF-TOPSIS				Proposed method	
	Distances from fuzzy PIS	Distances from fuzzy NIS	Revised closeness	Ranking	y_i	Ranking
Predictive Energy Optimization (A1)	0.047	0.086	-0.205	3	0.514	2
Smart Battery Management Systems (A2)	0.041	0.080	-0.133	1	0.546	1
AI-Optimized Route and Driving Assistance (A3)	0.067	0.092	-0.643	4	0.362	4
AI-Powered Regenerative Braking Optimization (A4)	0.072	0.069	-1.019	5	0.209	5
AI-Enabled Smart Charging and Grid Integration (A5)	0.044	0.082	-0.179	2	0.387	3
AI-Driven Thermal Management (A6)	0.083	0.071	-1.253	6	-0.100	6

The comparative results presented in Table 6 demonstrate a high degree of consistency between the PF-TOPSIS method and the proposed SWARA–Pythagorean Fuzzy MULTIMOORA framework. In both approaches, Smart Battery Management Systems (A2) is ranked as the most critical AI-based energy management strategy for electric vehicles, highlighting its universal importance across different evaluation techniques.

Additionally, AI-Driven Thermal Management (A6) consistently appears in the last position, indicating its relatively lower priority among the evaluated strategies in both methods. The positions of other alternatives, such as Predictive Energy Optimization (A1) and AI-Enabled Smart Charging and Grid Integration (A5), show slight variations (e.g., A1 is ranked second in the proposed method but third in PF-TOPSIS), yet the overall trend and grouping of alternatives remain largely aligned.

This alignment validates the robustness and reliability of the proposed methodology. The similarity in rankings across two distinct Pythagorean fuzzy MCDM techniques strengthens the credibility of the decision-making framework and validates the reliability of the weighting and ranking procedures employed in this study.

4. DISCUSSION (TARTIŞMA)

This study addresses a critical challenge in the transition toward sustainable transportation by evaluating AI-based energy management strategies for electric vehicles. As electric vehicles continue to gain prominence in global markets, optimizing their energy use through intelligent systems becomes increasingly essential for improving efficiency, performance, and environmental impact. The methodological strength of this study lies in the integration of the SWARA method and the Pythagorean Fuzzy MULTIMOORA approach. SWARA effectively captures expert judgment to assign meaningful weights to evaluation criteria, while the Pythagorean Fuzzy MULTIMOORA method offers a robust framework for handling uncertainty and imprecision in multi-criteria decision-making [20]. By combining these approaches, the study ensures both the reliability of the input data and the robustness of the final rankings, providing valuable insights for stakeholders aiming to adopt the most effective AI-based solutions in EV energy management.

As a result of the comprehensive evaluation, "Smart Battery Management Systems" emerged as the highest-ranked strategy among AI-based energy management solutions for electric vehicles. This outcome is largely due to the vital role these systems play in enhancing energy efficiency, prolonging battery life, increasing safety, and optimizing the overall operational performance of electric vehicles. Predictive maintenance, intelligent charging and discharging cycle control, and real-time monitoring are all made possible by smart battery management systems, and these features immediately reduce energy waste and long-term operating expenses. According to Ali et al. [21], a smart battery management system is one of the main parts of electric vehicles (EVs). It not only accurately assesses the battery's status but also ensures safe operation and prolongs its lifespan. For policy makers, these findings emphasize the importance of supporting initiatives and investments that facilitate the development and deployment of advanced battery technologies. Meanwhile, professionals in computer engineering and electrical and electronics fields can use this insight to guide innovation in AI algorithms, embedded systems, and battery health analytics. Focusing on this strategy can significantly accelerate the transition toward smarter, more sustainable, and user-friendly electric mobility solutions.

Following the computational analysis, "Predictive Energy Optimization" and "AI-Enabled Smart Charging and Grid Integration" rank as the second and third most critical AI-based energy management strategies for electric vehicles. Predictive energy optimization stands out for its ability to anticipate energy consumption based on dynamic factors such as driving behavior, road characteristics, and environmental conditions, allowing for proactive and efficient energy use. This strategy has been shown to significantly improve route planning and reduce energy consumption through data-driven models that combine machine learning and statistical approaches for real-world application [22]. Meanwhile, AI-enabled smart charging and grid integration play a vital role in aligning EV charging patterns with grid demands, enabling efficient load distribution and supporting the integration of renewable energy sources. These capabilities contribute to both operational cost reduction and enhanced grid stability, making this strategy indispensable in scaling EV infrastructure [23]. For policy makers, these findings offer a roadmap for prioritizing investments in predictive and intelligent charging technologies to enhance EV performance and sustainability. Professionals in engineering can strengthen these insights to drive innovation in AI models, smart infrastructure systems, and intelligent energy forecasting tools.

In the process of weighting the criteria for evaluating AI-based energy management strategies for electric vehicles, "Energy Efficiency" emerged as the most important criterion, followed by "Technological Integration" and "Economic Feasibility". "Energy efficiency" ranks first because it directly impacts the core goal of energy management—reducing consumption and maximizing the driving range of electric vehicles. As electric mobility continues to expand, ensuring optimal energy use is essential for both sustainability and performance. The importance of AI technologies in efficiently integrating with infrastructure, sensors, and vehicle systems is the reason "technological integration" is rated second. Without effective integration, even the most advanced AI models cannot be fully utilized. "Economic feasibility" takes the third spot, reflecting the practical necessity for cost-effective solutions that can be scaled and adopted by manufacturers and consumers alike. These insights are particularly valuable for policy-makers, as they highlight the need to support strategies that balance performance with technological innovation and cost. By prioritizing investments and incentives in areas that maximize energy savings and enable advanced technology deployment at a reasonable cost, policy-makers can drive the widespread adoption of efficient and intelligent energy solutions in the electric vehicle sector.

These findings offer valuable insights for both policy-makers and stakeholders in the electric vehicle industry by highlighting which AI-based energy management strategies and evaluation criteria are most critical for advancing sustainable and intelligent mobility. The prioritization of strategies such as smart battery management, predictive energy optimization, and intelligent charging systems underscores the need for supportive policies that encourage innovation in AI technologies and infrastructure development. Additionally, the emphasis on energy efficiency, technological integration, and economic feasibility as top evaluation criteria provides a clear framework for aligning regulatory actions, investment decisions, and research initiatives. For the electric vehicle industry, these insights help guide the development of next-generation energy management solutions that are not only technically effective but also economically viable and scalable.

5. CONCLUSION (SONUÇ)

This study holds significant importance as it addresses a critical and underexplored area in the field of electric vehicle development—the systematic evaluation and prioritization of AI-based energy management strategies. While existing literature has focused on individual components such as battery management, charging infrastructure, or general energy optimization, there remains a lack of comprehensive frameworks that assess these strategies in an integrated, comparative manner.

This study addresses that gap by integrating the SWARA method for determining the importance of evaluation criteria with the Pythagorean Fuzzy MULTIMOORA method for ranking alternative strategies. This hybrid approach enables a robust, flexible, and uncertainty-aware evaluation framework. The findings offer actionable insights for policy-makers, helping them prioritize investments and regulatory efforts that support sustainable and intelligent mobility solutions. Additionally, professionals in computer engineering and electrical and electronic engineering can use the results to guide the development of AI-driven technologies, including smart battery systems, predictive control algorithms, and intelligent charging infrastructure, all aimed at enhancing the performance and sustainability of electric vehicles.

The findings of this study reveal that among the evaluated strategies, “Smart Battery Management Systems” emerged as the most critical AI-based energy management solution for electric vehicles. This highlights the fundamental importance of intelligent battery control in enhancing energy efficiency, extending battery life, and ensuring overall system reliability. “Predictive Energy Optimization” ranked second, underscoring the value of AI-driven forecasting in managing energy consumption based on real-time driving conditions and user behavior. “AI-Enabled Smart Charging and Grid Integration” ranked third, reflecting the growing relevance of intelligent charging solutions that optimize load distribution and support the stability of the power grid. These results provide decision-makers with a data-driven framework for identifying the most impactful areas for policy development, research investment, and technological deployment. By prioritizing strategies with the highest potential for improving energy efficiency and system integration, stakeholders can make informed decisions that accelerate the transition toward intelligent and sustainable electric vehicle ecosystems.

Sensitivity analysis was also conducted to examine the robustness of the proposed decision-making framework. This involved modifying the criterion weights initially determined by the SWARA method and recalculating the Ratio System (RS) scores within the Pythagorean Fuzzy MULTIMOORA approach. A total of 21 distinct scenarios were created, each involving a pairwise exchange of weight values between two criteria to observe the resulting changes in strategy rankings. The findings of the sensitivity analysis demonstrate that, despite the weight alterations, the overall ranking of AI-based energy management strategies remained largely consistent. This stability confirms the reliability and robustness of the evaluation model, reinforcing confidence in the prioritization outcomes and supporting its application in real-world decision-making contexts related to electric vehicle energy strategy development.

This study provides a solid foundation for evaluating AI-based energy management strategies for electric vehicles; however, there are several promising directions for future research. Upcoming studies can be expanded by incorporating additional evaluation criteria to capture broader technical, economic, and social dimensions. Moreover, increasing the number and diversity of expert participants would enhance the reliability and generalizability of the results. The proposed methodology can also be applied to other decision-making problems within the transportation and energy sectors, such as evaluating smart grid technologies, sustainable mobility solutions, or alternative fuel systems. Methodologically, the framework can be enhanced by integrating alternative fuzzy set theories, such as Fermatean fuzzy sets or Spherical fuzzy sets, to better represent uncertainty in complex environments. Additionally, other multi-criteria decision-making (MCDM) methods, including CRITIC (CRiteria Importance Through Intercriteria Correlation) for objective weighting and MARCOS (Measurement of Alternatives and Ranking according to the Compromise Solution) for ranking alternatives, can be explored to further strengthen the decision-making process. Expanding the application of the proposed methodology across different regional or country-specific EV ecosystems could also offer valuable comparative insights for policymakers and practitioners. Moreover, scenario-based or dynamic decision-making frameworks can be incorporated to reflect real-world fluctuations in energy demand, battery performance, and grid interactions. These extensions would provide greater flexibility and depth in evaluating technological solutions in the evolving landscape of electric vehicle innovation.

DECLARATION OF ETHICAL STANDARDS

(ETİK STANDARTLARIN BEYANI)

The author of this article declares that the materials and methods they use in their work do not require ethical committee approval and/or legal-specific permission.

Bu makalenin yazarı çalışmalarında kullandıkları materyal ve yöntemlerin etik kurul izni ve/veya yasal-özel bir izin gerektirmediğini beyan ederler.

AUTHORS' CONTRIBUTIONS (YAZARLARIN KATKILARI)

***Gözde BAKİOĞLU*:** She conducted the processes of literature review, methodology, analysis, visualization, discussion, and writing of the article.

Literatür, yöntem, analiz, görselleştirme, tartışma ve makalenin yazım işlemini gerçekleştirmiştir.

CONFLICT OF INTEREST (ÇIKAR ÇATIŞMASI)

There is no conflict of interest in this study.

Bu çalışmada herhangi bir çıkar çatışması yoktur.

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