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Electric Vehicle Charging Station Positioning Problem: Multi-Criteria Decision Making Analysis with Entropy, CoCoSo and EDAS Methods

Elektrikli Araç Şarj İstasyonu Konumlandırma Problemi: Entropi, CoCoSo ve EDAS Yöntemleriyle Çok Kriterli Karar Verme Analizi

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Abstract

The increasing adoption of electric vehicles (EVs) underscores the critical need for an efficient and sustainable charging infrastructure. This study addresses the problem of optimal electric vehicle charging station (EVCS) location selection using a multi-criteria decision-making (MCDM) approach. Specifically, the Entropy, CoCoSo (Combined Compromise Solution), and EDAS (Evaluation Based on Distance from Average Solution) methods were applied to evaluate 25 potential locations in Altıeylül. The Entropy method was first employed to objectively determine the weight of each criterion based on their variability, ensuring that more significant factors had a greater impact on the final decision. Environmental, technical, and social criteria were incorporated to ensure that the selected sites would maximize accessibility, reduce air pollution, and enhance user convenience. The results revealed that Location_17 emerged as the top choice for EVCS placement based on both CoCoSo and EDAS rankings. While both methods provided consistent results for high-performing locations, significant discrepancies were observed for certain low-performing sites, highlighting the value of combining multiple MCDM methods. This study provides an informed framework for selecting optimal EVCS locations, offering a balanced evaluation of criteria, and contributes to the growing body of research on sustainable infrastructure planning for EVs.

Key Words: Electric Vehicle Charging Stations, Multi-Criteria Decision Making, Entropy, CoCoSo, EDAS

Jel Codes: C61, Q55, R41

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Özet

Elektrikli araçların giderek daha fazla benimsenmesi, verimli ve sürdürülebilir bir şarj altyapısına duyulan kritik ihtiyacın altını çizmektedir. Bu çalışma, çok kriterli karar verme yaklaşımını kullanarak optimum elektrikli araç şarj istasyonu yeri seçimi problemini ele almaktadır. Özellikle Entropi, CoCoSo ve EDAS yöntemleri Altıeylül ilçesindeki 25 potansiyel konumu değerlendirmek için uygulanmıştır. Entropi yöntemi ilk olarak her bir kriterin ağırlığını değişkenliklerine göre objektif olarak belirlemek için kullanılmış ve daha önemli faktörlerin nihai karar üzerinde daha büyük bir etkiye sahip olması sağlanmıştır. Seçilen sahaların erişilebilirliği en üst düzeye çıkarmasını, hava kirliliğini azaltmasını ve kullanıcı rahatlığını artırmasını sağlamak için çevresel, teknik ve sosyal kriterler dahil edilmiştir. Sonuçlar, Konum_17'nin hem CoCoSo hem de EDAS sıralamalarına göre elektrikli araç şarj istasyonu yerleşimi için en iyi seçenek olduğunu ortaya koymuştur. Her iki yöntem de yüksek performanslı yerler için tutarlı sonuçlar verirken, bazı düşük performanslı yerler için önemli farklılıklar gözlemlenmiş ve birden fazla ÇKKV yönteminin birleştirilmesinin değeri vurgulanmıştır. Bu çalışma, kriterlerin dengeli bir şekilde değerlendirilmesini sağlayarak optimum elektrikli araç şarj istasyonu konumlarının seçilmesi için bilinçli bir çerçeve sunmakta ve elektrikli araçlar için sürdürülebilir altyapı planlaması konusunda giderek artan araştırmalara katkıda bulunmaktadır.

Anahtar Kelimeler: Elektrikli Araç Şarj İstasyonları, Çok Kriterli Karar Verme, Entropi, CoCoSo, EDAS

Jel Kodları: C61, Q55, R4

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INTRODUCTION

EVs have emerged as a transformative solution in the pursuit of sustainable mobility, owing to their ability to significantly reduce air pollution and greenhouse gas emissions. This environmental benefit has spurred global interest in EV adoption as a means to diminish reliance on traditional internal combustion engine (ICE) vehicles. However, while the sales and demand for EVs continue to grow exponentially, the supporting infrastructure remains insufficient, particularly in comparison to the well-established fueling networks for ICE vehicles. The limited availability of public EV charging stations poses a substantial challenge to the widespread adoption of EVs, emphasizing the critical need for effective, accessible, and scalable charging infrastructure solutions (Dimitriadou et al., 2023, 7).

One of the key barriers to developing comprehensive EV infrastructure is the operational complexity of deploying charging stations in diverse urban and rural landscapes. Urban areas, in particular, face unique challenges due to space constraints, making it difficult to accommodate facilities for user charging, terminal charging, and depot charging. Effective decision-making in the placement of EV charging stations is crucial not only to meet current demand but also to drive further adoption of EVs by ensuring user convenience and accessibility. Urban infrastructure planning must consider user behavior patterns, including preferences related to travel time, proximity of stations, charger types, and pricing structures. Despite these advancements, there remains a gap in addressing charging station placement from the perspective of utility providers, whose involvement is pivotal in ensuring the scalability and economic feasibility of such projects (Dimitriadou et al., 2023, 7; Xiong et al., 2020, 2).

Government policies aimed at reducing air pollution, coupled with the volatility of fossil fuel prices, have accelerated the transition to EVs globally. Advances in battery technology, vehicle efficiency, and charging solutions have further enabled EVs to become a competitive alternative to ICE vehicles. Major automotive manufacturers have invested heavily in producing low-emission and zero-emission vehicles to meet both regulatory requirements and consumer expectations. For EV users, the accessibility and reliability of charging stations remain top priorities, as range anxiety continues to be a significant concern. To address these needs, many governments and private stakeholders have collaborated to develop robust charging networks that cater to both regular and emergency charging requirements. However, poorly planned infrastructure can result in underutilized stations and wasted resources, underscoring the need for strategic planning in network expansion (Zaino et al., 2024, 2).

As the adoption of EVs grows, the demand for well-placed charging infrastructure has become more pressing. The limited range of EVs makes the availability of charging stations a crucial factor in promoting their use in both personal and public transportation. Strategically distributed charging networks not only enhance user convenience but also play a vital role in reducing transportation-related carbon emissions. Research in this domain has highlighted various methodologies to optimize the placement of charging stations, focusing on maximizing environmental benefits, improving urban transportation efficiency, and meeting user expectations. MCDM methods have gained prominence for their ability to evaluate diverse criteria systematically, integrating environmental, social, and technical factors into the decision-making process.

In this context, Altıeylül, a district in Balıkesir, Turkey, provides a unique case study for EV charging station placement. With a population of approximately 185,458 as of 2023 (TÜİK, 2024). Altıeylül combines urban and rural characteristics, making it an ideal pilot region for evaluating EV infrastructure deployment in mixed-use territories. As part of the Balıkesir metropolitan area, the district retains the charm of smaller towns while facing the growing pressures of urbanization. A strategically located charging station in Altıeylül has the potential to significantly impact transportation patterns, encourage EV adoption, and mitigate local air pollution. Furthermore, the district's proximity to environmentally sensitive areas, such as nature reserves, underscores the importance of sustainable and environmentally conscious infrastructure planning.

To address the challenges of EV infrastructure development in Altıeylül, this study employs Entropy, CoCoSo, and EDAS methods to perform a comprehensive Multi-Criteria Decision-Making (MCDM) analysis. The analysis evaluates specific criteria critical to the successful placement of an EV charging station, including construction cost, demographic density, road accessibility, electric infrastructure, parking compatibility, traffic density, and land use. These factors reflect the complex interplay of economic, technical, and social considerations required to ensure the charging station is not only functional but also accessible and sustainable. By focusing on these detailed criteria, the study aims to identify a location that balances the practicalities of construction and operation with the broader goals of improving EV adoption and reducing local air pollution.

1. LITERATURE REVIEW

The increasing adoption of EVs has necessitated research into optimal site selection for EVCSs, focusing on MCDM approaches. MCDM methods are particularly effective for this problem as they allow for the systematic evaluation of multiple, often conflicting, criteria such as environmental impact, user accessibility, operational efficiency, and cost-effectiveness. These methods have been applied to prioritize attributes based on their relative importance and ensure that EVCS placement aligns with technical, social, and economic considerations.

Soczówka et al. (2024)'s focus on determining optimal locations for EVCSs using GIS tools, specifically in the city of Gliwice, Poland. While it emphasizes the use of spatial data and a hexagonal grid for analysis, it does not explicitly incorporate MCDM methods. Instead, the study aims to ensure equal access to charging infrastructure for all residents, highlighting this as a critical aspect of the EVCS location selection process.

Mazza et al. (2024) discuss the application of MCDM methods for determining the locations of EVCSs. The paper emphasizes that MADM is more suitable than multi-objective decision-making (MODM) for addressing this problem. Through a systematic literature review, the research identifies relevant attributes and features, assessing their relative importance based on frequency and assigned weights. This framework seeks to enhance the operational efficiency and service quality of EVCSs while accounting for geographical and market factors.

Krishankumar and Ecer (2024) present a MCDM framework for selecting optimal locations for EVCS within a double hierarchy linguistic context. The study employs the CRITIC technique to evaluate expert reliability, the attitudinal Cronbach's method to estimate criteria weights, and the CRADIS formulation to rank alternatives. Key criteria considered include service capability, ecological impact, land cost, and traffic density, with Manapparai, India, identified as the optimal location for new EVCS construction.

Mhana and Awad (2024) identify suitable locations for EVCSs in Baghdad and Riyadh using MCDM methods, specifically the Analytical Hierarchy Process (AHP) and Fuzzy-AHP (FAHP). In Baghdad, the identified locations include Karkh, Dora, Hurriya, Yarmouk, Binouk, and the area near Baghdad International Airport. In Riyadh, the recommended sites are Dhahrat Laban, Ash Shifa, Al-Sina'yah, Tuwaiq, Al-Olaya, and Al-Murabba. These locations were determined based on twelve criteria analyzed through GIS and multi-criteria decision analysis.

Men and Zhao (2024) present a hybrid preference-based methodology for locating EVCSs, integrating multiple optimization preferences from distribution network operators, charge station owners, and electric vehicle users. The study formulates the problem using an uncertain mixed-integer programming model with Type-2 fuzzy variables to address the multifaceted uncertainties in the charging process. This methodology effectively reconciles conflicting preferences among various stakeholders, highlighting the importance of incorporating multiple criteria in decision-making for EVCS location planning.

Sani et al. (2023) explore the integration of GIS with MCDM methods, specifically AHP, FAHP, and TOPSIS (Technique for Order Preference by Similarity to Ideal Solution), to identify optimal locations for EVCSs. The study focuses on four main criteria: environmental, geographical, urbanity, and transportation. These criteria are weighted and analyzed to determine the most suitable sites for EVCS, aiming to enhance the efficiency and effectiveness of electric vehicle charging infrastructure.

Zhang (2023) employ the AHP to evaluate key factors influencing the location of EVCSs. The study systematically compares these factors across different levels to develop a scientific evaluation model. Furthermore, it integrates a k-means clustering algorithm to categorize 12 typical enterprises, enabling personalized siting solutions tailored to the specific requirements of various charging station operators. This approach addresses challenges such as inefficient layouts and limited coverage, offering a more targeted and effective framework for siting decisions.

Zhao et al. (2023) propose a MCDM framework that integrates Geographic Information Systems (GIS) for the optimal site selection of EVCSs. The study establishes a site selection index system comprising four main aspects and ten sub-criteria. Weights are assigned to these criteria using the fuzzy DEMATEL method, while the fuzzy MULTIMOORA method is employed to rank potential sites. The model is validated through a case study in Qingdao, which identified eight preliminary sites and selected the most suitable locations for photovoltaic charging stations.

Advancements in MCDM approaches have introduced diverse methodologies to address the complexity of EVCS siting. Techniques such as AHP, FAHP, DEMATEL, MULTIMOORA, and CRADIS enable a structured evaluation of criteria and their interdependencies, providing robust frameworks for decision-making. CoCoSo and EDAS methods are particularly suitable for EVCS siting problems due to their ability to handle multi-faceted criteria and conflicting priorities. CoCoSo offers a balanced compromise by combining linear and geometric aggregations, providing robust and accurate rankings. EDAS focuses on evaluating alternatives based on their deviations from an average solution, making it highly effective in scenarios where relative performance against a benchmark is critical. These methods facilitate informed decision-making by addressing complex, multi-dimensional criteria in a systematic and efficient manner.

2. MATERIALS AND METHODS

2.1. Materials

This study relied on comprehensive datasets and carefully selected evaluation criteria to identify optimal locations for EVCSs. Seven critical criteria were considered to capture the social, technical, and economic dimensions of the problem. Construction cost was included to account for the expenses related to site preparation and installation, while demographic density reflected the population distribution and potential demand for EVCSs in various regions. Road accessibility ensured that locations were conveniently accessible via major roads and highways, and electric infrastructure evaluated the proximity of existing power grid infrastructure to minimize installation complexities and costs. Additionally, parking compatibility assessed the availability and suitability of parking spaces near proposed EVCS sites, traffic density provided insight into average traffic flow and potential station usage, and land use focused on ensuring compatibility with zoning regulations and future urban planning.

In this process, the role of stakeholders in the planning of electric vehicle charging station placement in the Altıeylül region is of critical importance. Contributions from various groups, ranging from local governments' traffic regulations and land allocation to energy distribution companies' infrastructure support, have directly impacted the success of the stations. The private sector has enabled the development of innovative charging technologies, while users have contributed to identifying needs through their feedback. Regulatory institutions, such as EPDK (Republic of Türkiye Energy Market Regulatory Authority), have played a crucial role by establishing technical standards to ensure that charging stations are compatible with all vehicle models, reliable, and user-friendly. These standards not only enhance the safety and energy efficiency of the infrastructure but also facilitate its quality control, ensuring long-term sustainability (ResmiGazete, 2022). Additionally, the analytical support provided by academic circles has guided the decision-making processes, contributing to a balanced and informed approach.

The dataset used in this study was compiled from publicly available sources and supplemented with simulated scenarios specific to Altıeylül, Balıkesir, Turkey. This dataset included economic data on construction costs and land values, demographic data on population density and distribution, and infrastructure data detailing road networks, electric grid accessibility, and parking facilities (Endeksa, 2024; TMMOB, 2022; TÜİK, 2024). Traffic data highlighted traffic density in potential EVCS zones, while land use data analyzed zoning regulations and land suitability for station placement (BalıkesirBüyükşehirBelediyesi, 2024). These materials provided a comprehensive foundation for evaluating and ranking potential EVCS locations.

Lastly, the materials were applied in a case study of Altıeylül to validate the feasibility of proposed EVCS sites. This contextual data ensured that the study accounted for real-world constraints and regional dynamics, providing actionable insights for decision-making in EVCS placement. The dataset used in this study represents 25 potential locations for EVCSs and includes seven evaluation criteria. Each criterion was normalized to ensure comparability, and the values reflect the relative suitability of each location. The dataset is detailed in Table 1.

Table 1. Evaluation Criteria and Normalized Values for Potential EVCS Locations

Locations	Construction Cost	Demographic Density	Road Accessibility	Electric Infrastructure	Parking Compatibility	Traffic Density	Land Use
Location 1	0.374540119	0.950714306	0.731993942	0.598658484	0.156018640	0.155994520	0.058083612
Location 2	0.866176146	0.601115012	0.708072578	0.020584494	0.969909852	0.832442641	0.212339111
Location 3	0.181824967	0.183404510	0.304242243	0.524756432	0.431945019	0.291229140	0.611852895
Location 4	0.139493861	0.292144649	0.366361843	0.456069984	0.785175961	0.199673782	0.514234438
Location 5	0.592414569	0.046450413	0.607544852	0.170524124	0.065051593	0.948885537	0.965632033
Location 6	0.808397348	0.304613769	0.097672114	0.684233027	0.440152494	0.122038235	0.495176910

Location 7	0.034388521	0.909320402	0.258779982	0.662522284	0.311711076	0.520068021	0.546710279
Location 8	0.184854456	0.969584628	0.775132823	0.939498942	0.894827350	0.597899979	0.921874235
Location 9	0.088492502	0.195982862	0.045227289	0.325330331	0.388677290	0.271349032	0.828737509
Location 10	0.356753327	0.280934510	0.542696083	0.140924225	0.802196981	0.074550644	0.986886937
Location 11	0.772244769	0.198715682	0.005522117	0.815461428	0.706857344	0.729007168	0.771270347
Location 12	0.074044652	0.358465729	0.115869060	0.863103426	0.623298127	0.330898025	0.063558350
Location 13	0.310982322	0.325183322	0.729606178	0.637557471	0.887212743	0.472214925	0.119594246
Location 14	0.713244787	0.760785049	0.561277198	0.770967180	0.493795596	0.522732829	0.427541018
Location 15	0.025419127	0.107891427	0.031429186	0.636410411	0.314355981	0.508570691	0.907566474
Location 16	0.249292229	0.410382923	0.755551139	0.228798165	0.076979910	0.289751453	0.161221287
Location 17	0.929697652	0.808120380	0.633403757	0.871460590	0.803672077	0.186570059	0.892558998
Location 18	0.539342242	0.807440155	0.896091300	0.318003475	0.110051925	0.227935163	0.427107789
Location 19	0.818014766	0.860730583	0.006952131	0.510747303	0.417411003	0.222107810	0.119865367
Location 20	0.337615171	0.942909704	0.323202932	0.518790622	0.703018959	0.363629602	0.971782083
Location 21	0.962447295	0.251782296	0.497248506	0.300878310	0.284840494	0.036886947	0.609564334
Location 22	0.502679023	0.051478751	0.278646464	0.908265886	0.239561891	0.144894872	0.489452760
Location 23	0.985650454	0.242055272	0.672135547	0.761619615	0.237637544	0.728216349	0.367783133
Location 24	0.632305831	0.633529711	0.535774684	0.090289770	0.835302496	0.320780065	0.186518510
Location 25	0.040775142	0.590892943	0.677564362	0.016587829	0.512093058	0.226495775	0.645172790

2.2.Methods

MCDM is one of the most effective approaches for addressing complex decision-making problems, especially those involving multiple, often conflicting criteria related to the nature of decision alternatives (Karaşan et al., 2020, 4554). In this study, the primary objective is to select the most optimal location for an EVCS among various alternatives. MCDM methods, relying on relative preferences, prior knowledge, expert opinions, or simulated data, play a crucial role in defining the priority of decision alternatives across various domains. The choice of a specific MCDM method depends on the theoretical framework or practical conditions of the problem.

MCDM methods are particularly valuable in problems that include conflicting criteria, as they provide a systematic and practical framework to identify realistic, reasonable, and viable options, even in complex scenarios. The flexibility of these methods allows decision-makers to adapt their approaches depending on the context in which the decision is being made. This study applies the Entropy, CoCoSo, and EDAS methods, as they are widely recognized for their contributions to the relevant literature and their suitability for addressing the EVCS location problem in Altıeylül. These methods enable a structured and interdisciplinary evaluation of criteria, ensuring optimized placement of EVCSs even within the constraints of a limited budget.

The foundation of this approach is identifying and prioritizing the selection criteria, as determining the criteria plays a pivotal role in MCDM. The positioning of an EVCS involves integrating priority states across different decision-making elements. Each criterion and alternative is assessed based on various decision-making processes to align the final decision with technical, social, and economic considerations.

In MCDM processes, alternatives are evaluated based on a set of criteria rated under varying conditions. This approach requires addressing differing standards, sometimes conflicting criteria, and various decision-maker perspectives. Identifying relevant criteria is the first and most critical step, often informed by expert inputs and the dimensions of the problem. For each criterion and alternative, judgment values can vary or remain constant, depending on the decision-making context. This flexibility allows for the application of both crisp and fuzzy decision-making perspectives, depending on the complexity of the problem (Sahoo & Goswami, 2023, 27).

The methods employed in MCDM are diverse, ranging from those designed for partial or local optimization to comprehensive, global optimization techniques. These methods have been widely applied in various fields such as engineering, computer science, and environmental planning. They can also be used in uncertainty analysis, where influential criteria are identified and weighted based on their significance. For instance, in addition to assigning weights to criteria, the relative scores of alternatives can be analyzed to reveal their respective advantages and disadvantages. These weighted configurations offer a structured way to assess alternatives, making MCDM a powerful tool for addressing multifaceted decision-making challenges (Taherdoost & Madanchian, 2023, 78).

The use of Entropy, CoCoSo, and EDAS methods in this study ensures a comprehensive evaluation of criteria, balancing conflicting priorities and providing robust rankings of alternatives. These methods support the identification of criteria that are most critical to the EVCS location problem, such as accessibility, environmental impact, and cost efficiency. By systematically weighting and ranking alternatives, this approach highlights the advantages and disadvantages of each option, enabling an informed and efficient decision-making process that aligns with both local needs and broader sustainability goals.

2.2.1. Shannon's Entropy

Entropy, a measure of uncertainty, originates from information theory and quantifies the information contained within a system. In the context of MCDM, entropy provides an objective mechanism for determining the weights of criteria, highlighting the extent to which multiple criteria are distinct from or associated with one another. Improperly assigned weights that fail to reflect actual differences between criteria can introduce biases, potentially compromising the reliability of final decisions. The entropy method mitigates these biases by utilizing information processing techniques applied to evaluation matrices, offering a robust alternative to subjective weight assignment methods.

Entropy's strength lies in its foundation on non-relational information measures, which emphasize the variability and uncertainty present in the distribution of data across the evaluation system. By linking informational uncertainty to the distributional characteristics of criteria, entropy provides a systematic approach for integrating uncertainty management within the MCDM framework. This allows the entropy method to objectively assess the relative importance of each criterion in evaluating alternatives, making it a valuable tool in MCDM.

However, the entropy method is not without its limitations. The quality and distribution of data can significantly influence its effectiveness, as scattered or poor-quality data may distort weight calculations. To address these limitations, adjustments such as preprocessing techniques and complementary methods can be employed, ensuring that entropy-based analyses maintain their robustness and reliability in various MCDM applications.

Shannon's entropy and its related procedures are completely described below (Torkayesh et al., 2021, 6):

Step 1 – The initial decision matrix is normalized based on Eq. (1).

$$r_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \quad i = 1,2, \dots, m \tag{1}$$

Step 2- The entropy of each criterion is calculated using Eq. (2).

$$e_j = -K \sum_{i=1}^{m} r_{ij} \; log r_{ij} \; , j = 1,2 \dots, n \tag{2}$$

where is $K = \frac{1}{logm}$ is a constant that ensures $0 \leq e_j \leq 1$.

Step 3- Using Eq. (3), the weight of each criterion can be calculated accordingly.

$$\xi_j = \frac{1 - e_j}{\sum_{i=1}^{m} (1 - e_j)}, j = 1,2 \dots, n \tag{3}$$

where e_j represents entropy of each criterion calculated in the previous step.

2.2.2. CoCoSo

The CoCoSo method is a robust approach within the MCDM framework and is well-suited for complex decision-making scenarios involving multiple criteria. CoCoSo allows for the integration of diverse criteria, both qualitatively and quantitatively, making it a versatile tool in addressing intricate problems. Unlike other MCDM methods, CoCoSo emphasizes compromise by combining linear and geometric aggregations, offering a balanced evaluation that is robust against outliers. Its structure facilitates systematic decision-making, ensuring accuracy and consistency in ranking alternatives.

The method is particularly advantageous in problems requiring a balance between conflicting criteria, making it widely applicable in areas such as green building assessments, government procurement, supplier selection, and innovative technology evaluations. By leveraging its aggregation capabilities, CoCoSo ensures that decision-making processes are both flexible and coherent, producing results that align with the priorities of the evaluation criteria.

The CoCoSo process typically begins with a systematic evaluation of alternatives based on specified criteria. The method then aggregates rankings derived from linear and geometric means to compute a final compromise score. This balanced approach enables the decision maker to account for diverse influences while minimizing bias. Additionally, CoCoSo assigns proportional weights to criteria to maintain the integrity of the decision-making process. This proportional weighting mechanism, while effective, can present challenges in terms of achieving consensus on the assigned weights, particularly in scenarios where stakeholder input is critical.

Despite its advantages, the CoCoSo method is not without limitations. Assigning appropriate weights to criteria remains a challenge, as it often depends on expert judgment and proportional weightings, which may not always reflect stakeholder preferences accurately.

The following steps are used to solve CoCoSo decision problem (Bagal et al., 2021, 477-479):

1. Determination of initial decision-making matrix using Eq. (4)

$$X_{ij} = \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1n} \\ x_{21} & x_{22} & \dots & x_{2n} \\ \dots & \dots & \dots & \dots \\ x_{m1} & x_{m2} & \dots & x_{mn} \end{bmatrix} \tag{4}$$

2. Using compromise normalization equation, normalization of criteria values is done:

$$r_{ij} = \frac{x_{ij} - minx_{ij}}{maxx_{ij} - minx_{ij}}; \text{ for benefit criterion} \tag{5}$$

$$r_{ij} = \frac{maxx_{ij} - x_{ij}}{maxx_{ij} - minx_{ij}}; \text{for cost criterion} \tag{6}$$

3. Determination of total weighted comparability sequence and whole of power of weight of comparability sequences for respective alternate as Si and Pi, respectively:

$$S_i = \sum_{j=1}^{n} (w_j r_{ij}) \tag{7}$$

$$P_i = \sum_{j=1}^{n} \left(r_{ij}\right)^{w_j} \tag{8}$$

4. Three appraisal score are used for generation of comparative weights of other options derived using Eqs. (9, 10, 11):

$$k_{ia} = \frac{P_i + S_i}{\sum_{i=1}^{m} (P_i + S_i)} \tag{9}$$

$$k_{ib} = \frac{S_i}{minS_i} + \frac{P_i}{minP_i} \tag{10}$$

$$k_{ic} = \frac{\lambda(S_i) + (1-\lambda)(P_i)}{(\lambda maxS_i + (1-\lambda)maxP_i)} \tag{11}$$

5. Ranking of all alternatives is determined from higher to lower based on ki values:

$$k_i = (k_{ia} k_{ib} k_{ic})^{\frac{1}{3}} + (k_{ia} + k_{ib} + k_{ic}) \tag{12}$$

2.2.3. EDAS

EDAS is a simple, practical, and effective method that can be easily utilized and improved by decision-makers. In the EDAS model, alternatives are evaluated based on their Manhattan distances from the average solution, providing valuable insights and results for positioning EV charging stations. This method has distinct advantages, making it a suitable choice for MCDM problems. For instance, EDAS is computationally efficient and relatively straightforward to apply, even for complex decision-making scenarios. Its reliance on an average solution allows for a clear comparison of alternatives and facilitates prioritization based on their positive or negative deviations. Moreover, EDAS results are objective and easy to interpret, making it highly practical for real-world applications.

However, the method is not without its limitations. One of its primary challenges lies in determining an ideal solution, especially for complex problems like EV charging station placement, where criteria are often subjective and context-specific. While EDAS evaluates alternatives based on deviations from an average solution, it does not consider interdependencies or correlations between criteria, which may influence the decision-making process. Additionally, the outcomes of EDAS are sensitive to the criteria weights and the chosen reference values, which may lead to variability in results. These limitations suggest that EDAS is best utilized as part of a broader decision-making framework, where its results can be complemented with additional analyses or methods that address these challenges.

The outputs of the EDAS model assist decision-makers in identifying alternatives that are either satisfying or critical for achieving optimal placement. These results can also serve as a foundation for incorporating evaluation weights, preferences, and constraints into other MCDM approaches, further enriching the analysis and supporting a more robust decision-making framework.The evaluation based on distance from the average solution (EDAS) method is one of the important parts of the MCDM framework. It works by assessing alternatives with respect to the distance of the alternatives from the ideal solution. The steps of using the EDAS are shown below (Bagal et al., 2021, 480-482):

Step 1: Select the most important criteria that describe alternatives.

Step 2: Construct the decision-making matrix (X), shown as follows:

$$X = \left[x_{\text{ij}}\right]_{n*m} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2m} \\ \cdots & \cdots & \cdots & \cdots \\ x_{n1} & x_{n2} & \cdots & x_{nm} \end{bmatrix} \tag{13}$$

where X_{ij} denotes the performance value of ith alterative on jth criterion.

Step 3: Determine the average solution according to all criteria, shown as follows:

$$AV = [AV_j]_{1*m} \tag{14}$$

Where,

$$AV_j = \frac{\sum_{i=1}^{n} X_{ij}}{n} \tag{15}$$

Step 4: Calculate the positive distance from average (PDA) and the negative distance from average (NDA) matrixes according to the type of criteria (benefit and cost), shown as follows:

$$PDA = \ [PDA_{ij}]_{n*m} \tag{16}$$

$$NDA = \ [NDA_{ij}]_{n*m} \tag{17}$$

if jth criterion is beneficial,

$$PDA_{ij} = \frac{\max\left(0,(X_{ij} - AV_j)\right)}{AV_j} \tag{18}$$

$$NDA_{ij} = \frac{\max\left(0,(AV_j - X_{ij})\right)}{AV_j} \tag{19}$$

and if jth criterion is non-beneficial,

$$PDA_{ij} = \frac{\max\left(0,(AV_j - X_{ij})\right)}{AV_j} \tag{20}$$

$$NDA_{ij} = \frac{\max\left(0,(X_{ij} - AV_j)\right)}{AV_j} \tag{21}$$

where PDA_{ij} and NDA_{ij} denote the positive and negative distance of ith alternative from average solution in terms of jth criterion, respectively.

Step 5: Determine the weighted sum of PDA and NDA for all alternatives shown as follows:

$$SP_{\text{i}} = \sum_{\text{j}=1}^{m} w_j PDA_{ij} \tag{22}$$

$$SN_{\text{i}} = \sum_{\text{j}=1}^{m} w_j NDA_{ij} \tag{23}$$

where wj is the weight of jth criterion.

Step 6: Normalize the values of SP and SN for all alterative, shown as follows:

$$NSP_i = \frac{SP_i}{max_i(SP_i)} \tag{24}$$

$NSN_i = 1 - \frac{SN_i}{max_i(SN_i)}$ (25)

Step 7: Calculate the appraisal score (AS) for all alterative, shown as follows:

$AS_i = \frac{1}{2}(NSP_i + NSN_i)$ (26)

where $0 \leq AS_i \leq 1$.

Step 8: Rank the alternatives according to the decreasing values of appraisal score (AS). The alternative with the highest AS is the best choice among the candidate alternatives.

3. RESULTS

The Entropy Method was applied to determine the relative importance of each criterion. This method calculates weights based on the variability and distribution of the data for each criterion. Criteria with higher variability (greater discrimination power) were assigned higher weights, while those with lower variability received lower weights.

The calculated weights for the seven criteria are as follows:

Table 2. Entropy-Calculated Weights for EVCS Evaluation Criteria

Criterion	Weight
Construction Cost	0.18406
Demographic Density	0.145122
Road Accessibility	0.164271
Electric Infrastructure	0.128029
Parking Compatibility	0.113917
Traffic Density	0.135731
Land Use	0.12887

These weights were incorporated into the dataset to prepare for further analysis. Each location's normalized values for the criteria (e.g., Construction Cost, Demographic Density, etc.) were weighted accordingly. This ensures that the significance of each criterion is accurately reflected in the ranking process.

The next phase involves applying the CoCoSo and EDAS methods to rank the 25 potential EVCS locations. These methods will use the weighted dataset to evaluate the alternatives and provide a comprehensive ranking based on their suitability. The results will highlight the most optimal locations for EVCS placement based on the selected criteria and calculated weights.

The results of the analysis comparing CoCoSo and EDAS methods for ranking potential EVCS locations are presented in Table 3. The table includes both the raw scores and normalized scores derived from each method, allowing for a comprehensive evaluation of the rankings and their alignment.

The CoCoSo method evaluates locations based on a compromise aggregation of linear and geometric means, while EDAS assesses the deviations of alternatives from an average solution, distinguishing between positive and negative performance. In the rankings, Location_17 emerged as the most suitable site for EVCS placement, achieving the highest normalized score of 1.0 in both CoCoSo and EDAS methods. This consistency indicates its robustness as a top-performing location across both evaluation frameworks. Similarly, Location_8 followed closely with normalized scores of 0.9925 (CoCoSo) and 0.9960 (EDAS), making it another strong contender for EVCS placement.

However, certain locations displayed notable discrepancies between the methods. For example, Location_24 achieved a moderate normalized score of 0.652 in CoCoSo but a negative normalized score of -0.0094 in EDAS, indicating that while CoCoSo considers it a moderately favorable option, EDAS evaluates it as underperforming relative to the average solution. Such discrepancies can be attributed to the differing computational logics of the two methods, with CoCoSo favoring balanced overall performance and EDAS penalizing locations with below-average performance in specific criteria.

Furthermore, several locations, including Location_9 and Location_15, were ranked poorly by both methods. These sites not only had low normalized CoCoSo scores (0.3681 and 0.4245, respectively) but also exhibited significantly negative EDAS scores (-0.8114 and -0.6249). This consistent underperformance indicates that these locations are among the least suitable for EVCS placement.

The comparative analysis highlights the strengths and limitations of the two methods. CoCoSo provides a balanced evaluation by aggregating performance across all criteria, while EDAS offers insights into deviations from an average benchmark, making it particularly sensitive to underperforming locations. The alignment of results for top-performing locations like Location_17 and Location_8 suggests that these are robust options, suitable for EVCS placement under different evaluation paradigms. Meanwhile, the divergence in rankings for locations such as Location_24 and Location_22 underscores the importance of considering multiple methods in MCDM processes for EVCS site selection.

These findings offer valuable insights for decision-makers, enabling them to identify the most suitable EVCS locations while recognizing the influence of methodological differences on ranking outcomes.

Table 3. Detailed Comparison of CoCoSo and EDAS Rankings

Location	CoCoSo_Score	EDAS_Score	CoCoSo_Score_Norm	EDAS_Score_Norm	CoCoSo_Rank	EDAS_Rank	Rank_Difference
Location_17	0.034784025	0.537902521	1	1	1	1	0
Location_8	0.034523815	0.535764023	0.988161596	0.99780526	2	2	0
Location_14	0.030110956	0.296325155	0.787395933	0.752069237	3	3	0
Location_2	0.029913724	0.281177433	0.77842274	0.736523136	4	4	0
Location_23	0.029505041	0.231648402	0.759829472	0.68569151	5	5	0
Location_20	0.027097798	0.211620692	0.650310496	0.665137078	6	6	0
Location_11	0.025477789	0.143246423	0.576607232	0.594964591	7	7	0
Location_18	0.024165334	0.049327757	0.516896293	0.498575899	8	8	0
Location_5	0.024132417	0.016410101	0.515398722	0.46479252	9	10	-1
Location_13	0.023639406	0.030532882	0.49296889	0.479286725	10	9	1
Location_24	0.022685523	-0.00504528	0.4495714	0.44277287	11	11	0
Location_1	0.021204681	-0.073009272	0.382199585	0.373021451	12	12	0
Location_21	0.020885726	-0.106879586	0.367688557	0.338260359	13	15	-2
Location_7	0.020663005	-0.088185871	0.357555723	0.357445712	14	13	1
Location_10	0.020268871	-0.090229938	0.339624366	0.355347887	15	14	1
Location_6	0.019763722	-0.142610021	0.316642313	0.301590227	16	17	-1
Location_19	0.019742806	-0.120440549	0.315690723	0.324342748	17	16	1
Location_4	0.017357071	-0.249032376	0.20715028	0.192369003	18	20	-2
Location_25	0.01731688	-0.213157539	0.205321751	0.229187335	19	18	1
Location_22	0.017137938	-0.24444676	0.197180677	0.197075219	20	19	1
Location_3	0.016407395	-0.294550763	0.163944205	0.145653499	21	21	0
Location_16	0.016065315	-0.319029501	0.148381078	0.120530979	22	22	0
Location_12	0.014780981	-0.337365954	0.089949512	0.101712284	23	24	-1
Location_15	0.014764694	-0.336120808	0.089208521	0.102990177	24	23	1
Location_9	0.012803877	-0.436471791	0	0	25	25	0

Figure 1 illustrates the relationship between the normalized scores assigned to potential EVCS locations by the CoCoSo and EDAS methods. Each point on the scatter plot represents a specific location, with the CoCoSo scores on the x-axis and EDAS scores on the y-axis. The plot demonstrates a general positive correlation between the two methods, indicating a degree of consistency in how high-performing and low-performing locations are evaluated. Locations with higher CoCoSo scores tend to also achieve higher EDAS scores, as evidenced by the upward trend in the data points. At the top-right corner of the plot, locations with the highest scores from both methods cluster together, highlighting the most suitable sites for EVCS placement. However, for lower-scoring locations, the methods exhibit some divergence, with EDAS assigning lower or negative scores to locations that deviate significantly from the average solution, while CoCoSo retains positive but lower scores. This difference reflects the unique evaluation frameworks of the two methods—CoCoSo's balanced aggregation approach versus EDAS's focus on penalizing alternatives that deviate from the average solution. Overall, the correlation underscores the reliability of combining multiple MCDM methods for robust site selection, while also demonstrating the value of incorporating complementary approaches to capture nuanced performance differences among potential locations.

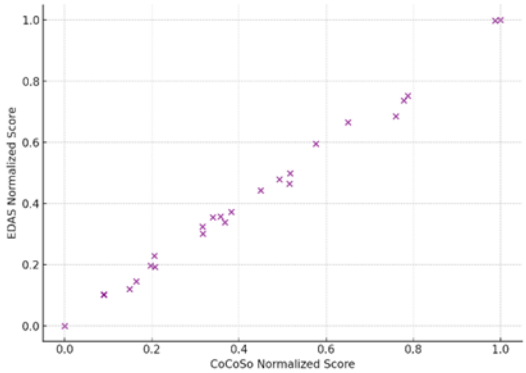

Figure 1. Correlation Between CoCoSo and EDAS Scores

Figure 2 provides a comparative analysis of the scores assigned to 25 potential locations for EVCSs using the CoCoSo and EDAS methods. The x-axis represents the candidate locations, while the y-axis displays the corresponding normalized scores from both methods. The comparison reveals consistency in identifying top-performing locations, such as Location_8 and Location_17, where both methods assign significantly higher scores, indicating their suitability for EVCS placement. However, noticeable divergences are observed for some lower-performing locations, such as Location_24, where CoCoSo assigns a moderately positive score, while EDAS results in a lower score. This discrepancy reflects the difference in methodological approaches: CoCoSo provides balanced and consistent scores by aggregating criteria, while EDAS penalizes alternatives that deviate below the average solution, resulting in greater score variability. Additionally, CoCoSo scores remain relatively stable across locations, whereas EDAS scores exhibit sharper fluctuations, highlighting its sensitivity to underperformance. This comparison underscores the complementary nature of the two methods, with CoCoSo offering a robust and balanced evaluation, and EDAS providing nuanced insights into deviations from average performance. Together, these methods enable a comprehensive and informed approach to EVCS site selection.

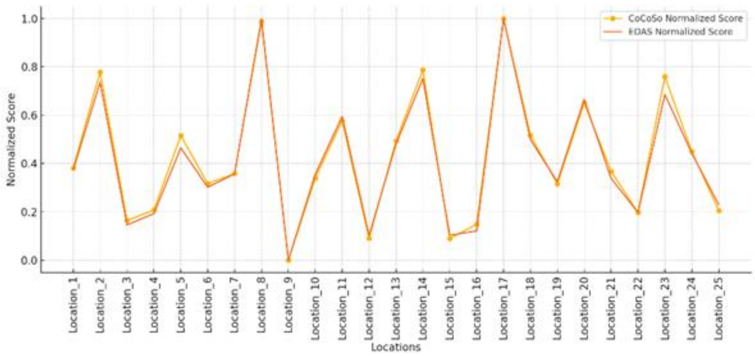

Figure 2. CoCoSo vs EDAS Score Comparison

Figure 3 presents a comparative analysis of the rankings assigned to 25 potential locations for EVCSs by the CoCoSo and EDAS methods. The x-axis represents the locations, while the y-axis indicates the rank assigned to each location, with lower ranks signifying higher suitability. The blue bars correspond to the CoCoSo rankings, and the green bars represent the EDAS rankings. The comparison reveals a strong alignment between the rankings generated by the two methods, particularly for the top-performing and bottom-performing locations. Locations such as Location_17 and Location_8 consistently achieve top ranks in both methods, indicating their robustness as optimal candidates for EVCS placement. However, minor variations are observed for certain mid-ranked and low-performing locations. For example, Location_24 and Location_25 exhibit noticeable differences in their CoCoSo and EDAS ranks, reflecting the distinct evaluation frameworks of the two methods. CoCoSo tends to provide more balanced rankings due to its aggregation approach, while EDAS introduces variability by emphasizing deviations from an average solution. This figure highlights the complementarity of the two methods. Their general agreement in rankings supports the reliability of the results, while the observed discrepancies emphasize the importance of using multiple evaluation methods to capture nuanced differences in site performance. Such an approach strengthens decision-making processes by providing a comprehensive understanding of the relative suitability of potential EVCS locations.

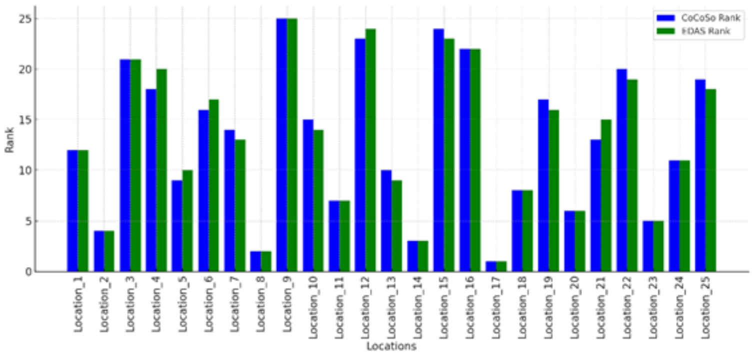

Figure 3. Ranking Comparison: CoCoSo vs EDAS

Figure 4 depicts the variation in rankings assigned by the CoCoSo and EDAS methods for 25 potential locations for EVCSs. The x-axis represents the locations, while the y-axis shows the rank differences calculated as CoCoSo Rank−EDAS Rank. A rank difference of 0 (highlighted by the red dashed line) indicates perfect agreement between the two methods for a given location. The figure reveals that for many locations, such as Location_17 and Location_8, the rank differences are close to zero, demonstrating strong agreement between CoCoSo and EDAS in evaluating these locations as top-performing candidates. However, for certain locations, significant deviations are observed. For example, Location_4 and Location_20 show negative rank differences, meaning that EDAS ranks these locations higher (better) than CoCoSo. Conversely, locations like Location_25 and Location_24 exhibit positive rank differences, indicating that CoCoSo ranks these sites higher than EDAS. These discrepancies reflect the distinct evaluation approaches of the two methods. CoCoSo's ranking tends to aggregate overall performance in a balanced manner, while EDAS focuses on deviations from the average solution, leading to more pronounced penalties for underperforming locations. This analysis highlights the complementarity of the methods and underscores the importance of using multiple evaluation frameworks to capture a comprehensive perspective on the relative suitability of EVCS locations. The figure provides valuable insights into areas of alignment and divergence, enabling more informed decision-making in site selection.

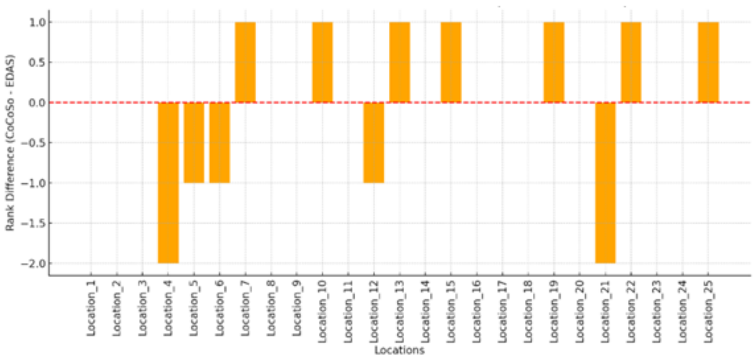

Figure 4. Rank Differences Between CoCoSo and EDAS

4. CONCLUSIONS

This study evaluated potential locations for EVCSs in Altıeylül, Turkey, employing MCDM techniques—Entropy, CoCoSo, and EDAS. By integrating environmental, technical, and social criteria, the analysis ensured a balanced evaluation that considered sustainability, accessibility, and cost-effectiveness. The findings demonstrated the utility of combining MCDM approaches to improve decision-making quality. CoCoSo provided a comprehensive and balanced assessment by aggregating diverse criteria, while EDAS captured deviations from an average solution, offering insights into areas requiring attention. The alignment between the two methods for top-performing locations, such as Location_17 and Location_8, validated their robustness as optimal EVCS sites. However, discrepancies in the rankings for lower-performing locations emphasized the importance of employing multiple methods to capture the complexities and variations in performance.

The broader implications of this study are significant for sustainable infrastructure development. It provides a practical framework for urban planners and policymakers to strategically deploy EVCSs, which could accelerate the adoption of electric vehicles and contribute to reduced carbon emissions. By addressing environmental, social, and technical factors, the proposed methodology aligns with global sustainability goals. Furthermore, the study highlights the potential of data-driven decision-making, with the Entropy method objectively assigning weights to criteria based on their variability, thus mitigating biases that can arise from subjective assessments. The focus on Altıeylül—a region with both urban and rural characteristics—also underscores the adaptability of the framework across diverse geographic contexts. The findings reinforce the critical role of well-positioned infrastructure in supporting EV adoption in mixed-use areas.

Looking forward, several recommendations for future research emerge from this work. Integrating GIS with MCDM methods could provide a dynamic evaluation by incorporating spatial data, leading to more precise identification of optimal EVCS locations. Additionally, involving stakeholders, such as local authorities, utility providers, and end-users, in the decision-making process could ensure that selected locations meet technical, economic, and user-centric needs. The scalability of the methodology could also be tested by applying it to other regions with varying levels of urbanization and transportation demands, providing a basis for context-specific adaptations.

Moreover, future research could explore the impacts of emerging technologies and policy frameworks on EVCS deployment. Technologies such as wireless charging and renewable energy integration could optimize EVCS operations and make them more sustainable. Similarly, analyzing the influence of policy measures on EVCS infrastructure planning could provide strategic insights for fostering electric mobility.

In conclusion, the integration of Entropy, CoCoSo, and EDAS methods in this study not only identifies optimal EVCS locations but also demonstrates the value of a multi-method approach in addressing complex infrastructure challenges. The proposed framework serves as a foundation for broader applications in transportation planning and sustainable development. As the global shift to electric mobility accelerates, this study contributes valuable insights for achieving efficient, accessible, and environmentally friendly charging infrastructure.

GENİŞLETİLMİŞ ÖZET

Araştırma Soruları ve Amaç

Elektrikli araçların artan benimsenmesi, verimli ve sürdürülebilir şarj altyapısına duyulan ihtiyacı artırmıştır. Bu çalışmanın amacı, elektrikli araç şarj istasyonlarının en uygun konumlarını belirlemek için objektif ve sağlam karar verme yöntemlerini kullanarak sistematik bir çerçeve geliştirmektir. Araştırma, elektrikli araç şarj istasyonu yer seçiminin nasıl optimize edilebileceği ve en uygun konumları belirlerken hangi kriterlerin en kritik olduğu gibi iki temel soruyu ele almaktadır. Bu çalışma, Altıeylül, Türkiye'yi bir vaka çalışması olarak ele alarak çevresel, teknik ve sosyal faktörlerin dengeli bir değerlendirmesinin sürdürülebilir altyapı planlamasına nasıl katkı sağlayabileceğini göstermeyi amaçlamaktadır.

Literatür Taraması

Elektrikli araçlara olan talebin artmasıyla birlikte şarj altyapısı için en uygun alanların belirlenmesi, şehir planlamacıları ve politika yapıcılar için önemli bir zorluk haline gelmiştir. Elektrikli araç şarj istasyonlarının etkili yerleştirilmesi, çevresel etki, erişilebilirlik, maliyet ve kullanıcı memnuniyeti gibi karmaşık bir dizi kriterin değerlendirilmesini gerektirir. Çok kriterli karar verme yöntemleri, birden fazla ve çoğu zaman çelişkili kriter temelinde alternatiflerin değerlendirilmesine yönelik yapılandırılmış çerçeveler sunarak bu zorlukların ele alınmasında etkili olmuştur. Soczówka ve arkadaşları (2024), elektrikli araç şarj istasyonlarının yerleştirilmesinde mekansal verilerin önemini vurgularken, şarj altyapısına eşit erişim ihtiyacını öne çıkarmıştır. Mazza ve arkadaşları (2024), hizmet kalitesi ve coğrafi faktörler gibi özelliklerin önceliklendirilmesinde çok kriterli karar verme yöntemlerinin avantajlarını göstermiştir. Krishankumar ve Ecer (2024), trafik yoğunluğu ve ekolojik etki gibi belirsizlikleri ele almak için çift hiyerarşi dilsel çok kriterli karar verme çerçevesi uygulamıştır. Men ve Zhao (2024), çeşitli paydaş tercihlerini entegre eden hibrit bir metodoloji sunmuş, Sani ve arkadaşları (2023) ise çevresel, kentsel ve ulaşım kriterlerini değerlendirmek için coğrafi bilgi sistemi ve çok kriterli karar verme entegrasyonunun etkinliğini sergilemiştir. Bu gelişmelere rağmen, Entropi yöntemi ile CoCoSo ve EDAS gibi gelişmiş sıralama yöntemlerinin entegrasyonu sınırlı kalmıştır. Bu çalışma, daha sağlam ve sistematik bir değerlendirme çerçevesi sunarak bu eksiklikleri gidermeyi amaçlamaktadır.

Yöntem

Bu araştırmada, Altıeylül, Türkiye'deki 25 potansiyel elektrikli araç şarj istasyonlarının lokasyonunu değerlendirmek için Entropi, CoCoSo ve EDAS olmak üzere üç çok kriterli karar verme yöntemi uygulanmıştır. Analiz için yedi kritik kriter seçilmiştir: inşaat maliyeti, demografik yoğunluk, yol erişilebilirliği, elektrik altyapısı, park uyumluluğu, trafik yoğunluğu ve arazi kullanımı. Entropi yöntemi, daha yüksek değişkenliğe sahip kriterlerin nihai sıralamalar üzerinde daha büyük bir etkiye sahip olmasını sağlamak için objektif ağırlıklar hesaplamak için kullanılmıştır. CoCoSo yöntemi, bu ağırlıkları birleştirerek her lokasyonun dengeli bir değerlendirmesini sağlamış, EDAS yöntemi ise alternatifleri bir ortalama çözümden sapmalarına göre değerlendirmiştir. Analiz için veriler, demografik istatistikler, altyapı verileri ve kentsel planlama veri setlerinden toplanmış, seçilen kriterlerin kapsamlı bir değerlendirmesi sağlanmıştır.

Bulgular ve Sonuçlar

Analiz, CoCoSo ve EDAS yöntemlerinde tutarlı bir şekilde en yüksek sırayı alarak Location_17'nin elektrikli araç şarj istasyonu için en uygun alan olduğunu belirlemiştir. Kullanıcı kolaylığını sağlamak ve altyapıdan en iyi şekilde faydalanmak için kritik olan erişilebilirlik ve demografik yoğunluk, bu kararda etkili olmuştur. Karşılaştırmalı sonuçlar, özellikle düşük sıradaki lokasyonlar için yöntemler arasındaki farklılıkları da vurgulamış ve birden fazla karar verme çerçevesinin birleştirilmesinin önemini göstermiştir. Bulgular, çelişen öncelikleri dengelemek ve veri odaklı kararlar almak için Entropi, CoCoSo ve EDAS yöntemlerinin etkinliğini doğrulamaktadır. Gelecekteki araştırmalar, yenilenebilir enerji entegrasyonu gibi ek kriterleri içerecek şekilde bu yaklaşımı geliştirebilir ve paydaşların katılımını sağlayarak kapsayıcılığı artırabilir. Bu çalışma, sürdürülebilir elektrikli araç şarj istasyonu yerleştirme için tekrarlanabilir bir model sunarak şehir planlamacıları ve politika yapıcılar için uygulanabilir içgörüler sunmaktadır.

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