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Comparative Performance Analysis of Algorithm Applications Used in Determining EVFCS Locations

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Abstract

With the increasing population, using petroleum and its derivatives in transportation has caused serious environmental problems, including global warming and urban air pollution. This situation has led to the widespread adoption of alternative fuel vehicles, especially Electric Vehicles (EVs), and determining station locations has become a popular research topic. Among the contributions of these studies to the literature are identifying the optimal locations for fast charging stations and space planning. Although numerous routing and charging calculation programs exist for EVs, nature-inspired optimization algorithms can be a valuable approach to addressing the challenges in routing and optimal placement. At the current stage of EV technology, when parameters such as vehicle range and available charging station locations are considered, there is a shortage of charging stations to facilitate efficient intercity travel. Therefore, determining the optimal locations for Electric Vehicles Fast Charging Stations (EVFCS) is a vital issue that needs to be addressed. Failure to identify optimal locations and to adequately plan fast charging stations may lead to problems for both EV owners and charging system operators, such as failing to meet charging demand at the desired level or underutilizing the planned fast charging stations. The main objective of station location planning is to obtain an optimal solution that maximizes the flow volume while simultaneously minimizing the installation costs of charging stations. This paper presents a comparative review of various EV optimal positioning techniques and algorithms used. In addition, it aims to determine the most suitable EVFCS points within the boundaries of Kavacik region of Beykoz district of Istanbul province by applying the geographical proximity-based Haversine algorithm and Analytical Hierarchy Process (AHP) algorithms, which are Multi-Criteria Decision-Making (MCDM) methods, separately.

Keywords: Electric Vehicle, Electric Vehicle Charging Station, Location Determination, Algorithms.

EAHŞİ Konumlarının Belirlenmesinde Kullanılan Algoritma Uygulamalarının Karşılaştırmalı Performans Analizi

Öz

Artan nüfusla birlikte ulaşımda petrol ve türevlerinin kullanılması, küresel ısınma ve kentsel hava kirliliği gibi ciddi çevresel sorunlara neden olmuştur. Bu durum, Elektrikli Araçlar (EA) başta olmak üzere alternatif yakıtlı araçların yaygın olarak benimsenmesine yol açmış ve istasyon konumlarının belirlenmesi popüler bir araştırma konusu haline gelmiştir. Bu çalışmaların literatüre katkıları arasında hızlı şarj istasyonları için en uygun yerlerin belirlenmesi ve alan planlaması yer almaktadır. EA'lar için çok sayıda rotalama ve şarj hesaplama programı mevcut olsa da doğadan ilham alan optimizasyon algoritmaları, rotalama ve optimum yerleştirmedeki zorlukları ele almak için değerli bir yaklaşım olabilir. EA teknolojisinin mevcut aşamasında, araç menzili ve mevcut şarj istasyonu konumları gibi parametreler göz önünde bulundurulduğunda, verimli şehirlerarası seyahati kolaylaştırmak için şarj istasyonu sıkıntısı yaşanmaktadır. Bu nedenle, Elektrikli Araç Hızlı Şarj İstasyonları (EAHŞİ) için en uygun konumların belirlenmesi, ele alınması gereken hayati bir konudur. Optimum konumların belirlenememesi ve hızlı şarj istasyonlarının yeterince planlanamaması hem elektrikli araç sahipleri hem de şarj sistemi operatörleri için şarj talebinin istenen düzeyde karşılanamaması veya planlanan hızlı şarj istasyonlarının yetersiz kullanılması gibi sorunlara yol açabilir. İstasyon yeri planlamasının temel amacı, akış hacmini en üst düzeye çıkarırken aynı zamanda şarj istasyonlarının kurulum maliyetlerini en aza indiren optimum bir çözüm elde etmektir. Bu makale, kullanılan çeşitli EA optimum konumlandırma teknikleri ve algoritmalarının karşılaştırmalı bir incelemesini sunmaktadır. Bunun yanında coğrafi yakınlık temelli Haversine algoritması ile Çok Kriterli Karar Verme (ÇKKV) yöntemi olan Analitik Hiyerarşi Süreci (AHP) algoritmalarını ayrı ayrı uygulayarak İstanbul ili Beykoz ilçesi Kavacık bölgesi sınırları içerisindeki en uygun EVFCS noktalarını belirlemeyi amaçlamaktadır.

Anahtar Kelimeler: Elektrikli Araç, Elektrikli Araç Şarj İstasyonu, Konum Belirleme, Algoritmalar.

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1. Introduction

The imminent depletion of fossil fuel resources has accelerated the adoption of EVs. The rapid increase in the use of EVs has led to a rise in the number of fast-charging stations. To accommodate this, it is necessary to expand the charging station infrastructure and increase the number of charging stations (YeniGün et al., 2023). The increasing global adoption of EVs indicates greater integration into the existing electricity distribution network, thereby increasing the importance of optimal scheduling strategies. Managing EV fast charging poses significant challenges, such as queue waiting times and power demand management (Petersen & Sax, 2022). The minimum number of fast charging stations on a road with a distance between any two points is expressed as the optimum positioning (Moghaddam & Akbari, 2022). Since EVs have longer charging times and shorter ranges compared to conventional vehicles, establishing a large charging station network can mitigate these issues. However, connecting numerous charging stations to the electricity grid will accelerate the increase in electricity demand, which is rising daily, especially regionally, in parallel with technological advancements (Kaya & Akar, 2024b). Variables such as charging limitations, the number of charging stations, fluctuations in electricity prices, charging times, and fast-charging capacities are considered when planning EV deployment (Hsaini et al., 2022; Alinia et al., 2019). Advanced techniques are required for planning, optimal location determination, and online selection of suitable charging stations (Nimalsiri et al., 2019; Koufakis et al., 2019).

In the literature, studies on charging stations are generally categorized into two main themes: the optimal placement of charging stations and the impact of these stations on the distribution network. Figure 1 illustrates the sub-study areas related to station placement and their effects on the distribution network (Nurmuhammed and Karadağ, 2021). He proposed a distributed charging method to manage congestion during the charging of EVs that demand energy from charging points connected to a grid with a distributed energy system (Zheng et al., 2025). Compared to conventional charging stations, battery swap stations offer faster charging times (Al-Zaidi and Inan, 2023). They provided a solution that considers both the vehicle's charging status and traffic conditions when directing EVs to appropriate fast charging stations. Additionally, they developed a system that suggests time-dependent travel speeds by taking into account congestion tolls (Zhang et al., 2020). They proposed a genetic algorithm based on minimization to determine the optimal locations of charging stations and the number of charges required at each station. Besides the costs associated with establishing charging stations, the model also considers transportation costs to the nearest station if there is no station at the driver's current location (Bouguerra and Layeb, 2019). They proposed a minimum-cost model and a solution algorithm to address two subproblems: the location optimization of charging and battery exchange stations for establishing infrastructure that supplies batteries for electric taxis. The proposed model was applied in Dalian, China (Guo et al., 2018). A multi-objective mathematical model was created to determine the optimum charging station locations, seeking to minimize the distance from each site to any station, the number of charging stations and the distance between them. This model was applied in Eskisehir province and solved using the weighted sum scalarization method. The aim of this work is to present a comprehensive approach to the optimal positioning of EV charging stations, including the selection of the best locations and the planning algorithms employed in various optimization methods (Yalcin et al., 2021). The energy consumption of electric motors in EVs is directly affected by geographical conditions. For example, between two points with an elevation difference, energy consumption will vary depending on whether the vehicle is traveling uphill or downhill. Therefore, some studies have considered geographical conditions and proposed the most suitable locations for charging stations (Raposo et al., 2015). Since both the hardware and operating costs of charging stations are high, increasing their utilization rates is essential. Consequently, selecting locations with higher traffic density can enhance utilization and allow operators to recover their investment in a shorter period. Thus, traffic density is a critical factor in the positioning of charging stations (Jordán et al., 2018). They developed a two-stage methodology to determine both the optimal number and placement of EV charging stations covering the entire road network in Italy. In the first stage, parameters such as autonomous vehicle behavior and range anxiety are used for the optimal location of stations, while in the second stage, parameters like amplification factor, number of charging sockets, and the number of vehicles that can be charged per day are considered to find the most reasonable number of fast charging stations (Micari et al., 2017). Figure 1 summarizes the parameters used for the optimum placement of EVFCSs in light of all these studies.

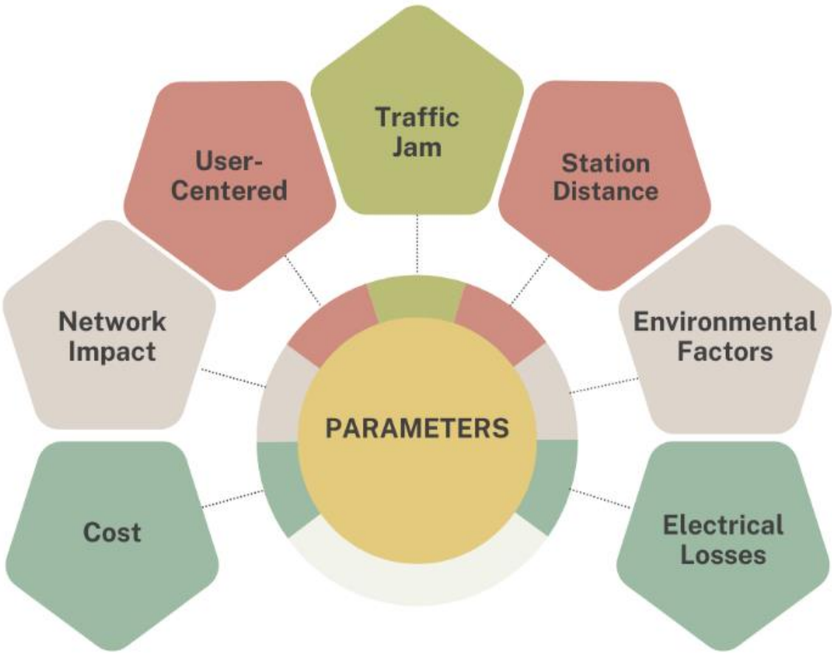

Figure 1. Fast Charging Station Location Optimization Research Parameters

2. Research and Findings

2.1. EVFCS Planning Approaches

An overview of optimal routing, charging planning approaches, algorithms, and mathematical models is presented in Figure 2, including pricing strategies, optimization approaches, and goal-oriented EV charging planning methods. The transportation sector is undergoing a radical transformation due to environmental concerns. Governments, EV companies, and energy providers are the primary actors EVs are becoming more and more in demand as time passes. The interaction between the transportation network and the electricity distribution network is governed by charging pricing and transportation planning, modeled through a cost-coordination optimization framework discussed in (Ding et al., 2020).

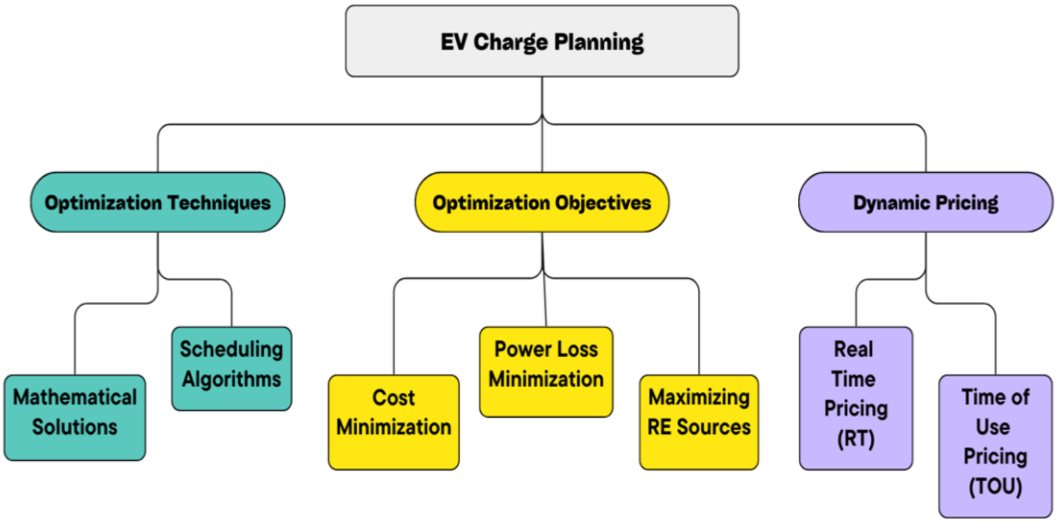

Figure 2. EVFCS planning approaches

The optimal siting problem of EV aggregators is modeled with EV owner satisfaction in mind, considering factors such as V2G operational costs, appropriate charging electricity prices, and the delivery of vehicles with fully charged batteries. This is recognized as an important issue in establishing a good pricing model that ensures the desired power withdrawal from the grid. An EV charging cost calculation has been developed that will benefit both end users and energy retailers (Aliasghari et al., 2019). An optimization model has been identified that covers the basic elements of EV services, such as operating in different time zones, service quality, multitasking, and time-varying charging prices. While designing this model, time-of-use rates and energy costs were also considered. In order to schedule EVs effectively, it is crucial to model the uncertainty in electricity costs. To address this, a robust optimal control approach for EV aggregators has been proposed (Cao et al., 2019b). Positioning algorithms aim to provide desired features such as improving energy efficiency, optimizing charging station range, and increasing ease of use to varying degrees. Additionally, negative factors such as user-related issues, computational complexities, and situations that make prediction difficult may be incorporated into the algorithms. These algorithms can vary in aspects such as efficiency, grid integration, real-time data adaptability, and scalability, making them suitable for specific use cases. When selecting the optimal EVFCS positioning algorithm, the objectives of the application environment, prioritized criteria, and limitations of the chosen algorithm should be carefully considered. Advances in research and technology aim to address these weaknesses and improve the overall performance and applicability of these algorithms (S. Lee and Choi, 2021).

2.2. Optimum Location Determination Methods

There are various methodologies for the optimal positioning of EVs. The smart grid model, which incorporates an optimization algorithm that considers wholesale strategies for EVs, demand conditions, local sales opportunities, electricity prices, and renewable energy generation options, facilitates decision-making for operators. As a result, the total operating cost has decreased by approximately 72% (Y. Liu et al., 2020). To obtain accurate results, the smart grid model should account for uncertain factors such as electricity markets, EV consumer behavior, demand levels, available storage systems, and generation capacities, all of which are constantly changing. Figure 3 illustrates the relative sources of uncertainty in optimal location problems (S. Guo et al., 2021).

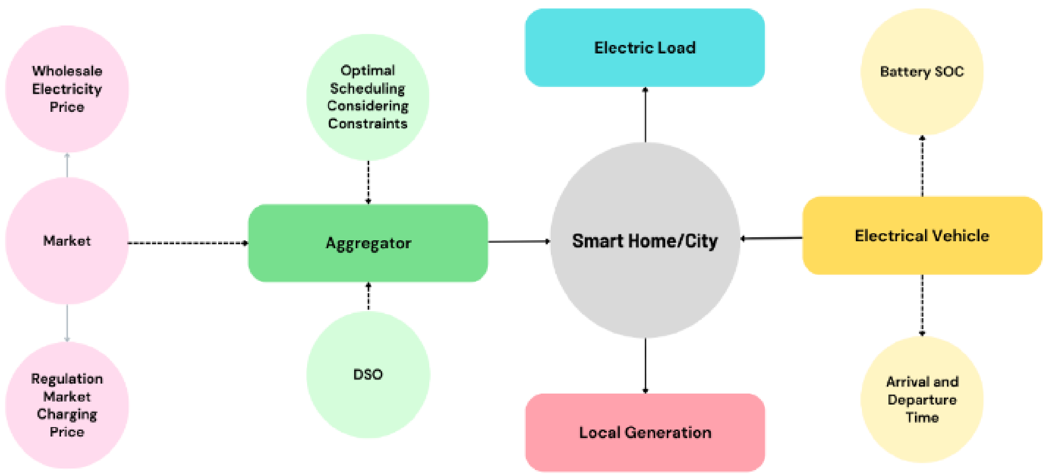

Figure 3. Relationship between sources of uncertainty in optimal location problems

An interactive program was developed to address the cost-reducing placement problem of an electric vehicle fast charging station (EVFCS) operator. As the number of EVFCS increases, it adds computational complexity to the program, making it challenging to solve with existing methods. Particularly in public areas, EVFCS are planned near workplaces to provide fast charging to fixed users. Research discusses how to optimize fast charging in a parking lot integrated with a PV system within the energy storage system. Charging optimization is performed through a formula aimed at reducing costs. Considering the stated limitations, a Grey Wolf Optimizer (GWO) was designed as the optimal positioning method, and an intelligent Binary Grey Wolf Optimizer (IBGWO) was used to improve the process by enhancing accuracy (Das et al., 2020).

2.3. Performance Comparison of EV Algorithms

The methodologies are compared by considering the different approaches used for optimal positioning, the various algorithms and mathematical models selected, as well as the technological tools employed, the benefits provided, and the practical drawbacks. Table 1 details the different implementation methods for the optimal positioning of EVs, including the operating cost based on a smart microgrid model. This approach aims to reduce transmission power fluctuations, thereby improving computational efficiency and scalability. Additionally, it helps avoid penalties and negative consequences due to reactive power consumption, improves voltage levels, and addresses congestion problems by minimizing charging costs (Mohammed et al., 2024; Shanmugam and Thomas, 2024).

Descriptions of the algorithms whose names are abbreviated in the tables are given below.

GA,	Genetic algorithm
VNS-DEPSO,	Variable neighborhood search differential evolutionary PSO
GSDA,	Gear shift delay algorithm
ACOMA,	Ant colony optimization metaheuristic algorithm
FLC,	Fuzzy logic control-based EV scheduling algorithm
HVNS,	Hybrid variable neighborhood search algorithm
MVDE,	Mixed-variable differential evolution algorithm
ANEC,	Augmented non-dominated ε-constraint algorithm
GA-SOOM,	Genetic algorithm based single-objective optimal modeling
GTA,	Game theory approach
MWA,	Max-weight algorithm
SP-BA,	Stochastic programming-based algorithm

ADMM,	Alternating direction method of multipliers algorithm
ABSA,	Ant based swarm algorithm
TSMA,	Task swap mechanism algorithm
COA,	Convex optimization algorithm
HA,	Heuristic algorithms
CCA,	Consensus coordination algorithm.

Table 1. Comparison of Algorithms Used for Optimal Positioning of EVs

Algorithms	Advantages	Disadvantages	References
GA	Reduce peak demand prices, energy losses, and transformer aging	The hedging advantage of EV owners is being lost and is considered a penalty cost	**(C. Guo et al., 2019)**
VNSDEPSO	Decrease operating costs of SMGs in undetermined environments.	The number of evaluations is restricted	**(Li et al., 2024)**
GSDA	Attempting to evade continuous gear changes and boost the riding/driving acquaintance	Increased fuel consumption	**(Bhadoria and Marwaha, 2022)**
ACOMA	Cut down the comprehensive latencies of the timing problem	Unsteady charging ratio not taken into account	**(Cheng et al., 2023)**
FLC	Unravel the EV jam problem and decrease wait duration	Weak charging demand ratio	**(Beheshtikhoo et al., 2023)**
HVNS	Uplifting the transports distribution network system by involving ambiguity	More working duration is necessary	**(Nejati et al., 2021)**
MVDE	Charging costs and SOC deficit of all EVs	MVDE should abandon the recent forecast in order to optimize the many others.	**(Wang and Chen, 2019)**
ANEC	Minimise battery deterioration	Sustainability must be developed	**(Zhou et al., 2020)**
GA-SOOM	Look for the best trade-off between G2V and V2G working expenses	The demand for additional power in the grid varies irregularly and fluctuates sharply	**(Singh et al., 2021)**

Table 2 below presents the operational implementation of various algorithms for EV optimal positioning. The appropriateness of EV routing and positioning algorithms stands on user-induced variants and the characteristics of the specified plan. Disparate algorithm options can be considered by taking into account factors such as the suitability of the charging infrastructure, user demands, environmental conditions, and the capacity of the number of EVs (Shanmugam and Thomas, 2024; Azzouz and Hassen, 2023).

Table 2. Parameters And Functions of The Algorithms Used for Optimal Positioning of EVs

Algorithms	Operational Aspects	Parameters	References
GTA	Load management, reduction of EV charging costs, Distribution network voltage control	Estimated locations, changeable tariff, distribution network characteristics, flexibility characteristics	**(Paudel et al., 2022)**
MWA	Load arrangement	Fexibility characteristics, changeable tariff	**(Alabi et al., 2022)**
SP-BA	Load arrangement	Predicted states, flexibility characteristics	**(Jamgochian et al., 2019)**
ADMM	Load arrangement, considering overload	Forecasted situations, grid characteristics, flexibility characteristics,	**(Mahyari and Freeman, 2025)**
ABSA	Load arrangement considering overload limits	Grid characteristics, flexibility characteristics, V2G backing	**(Wang et al., 2019)**
TSMA	Compensation management	Grid characteristics, changeable tariff backing V2G	**(Xia et al., 2025)**
COA	Increasing user comfort, reducing operating power costs to a minimum	Foreseen circumstances, grid characteristics, flexibility characteristics	**(Shen et al., 2021)**
HA	Maximising operational efficiency, fair remuneration	Grid characteristics, flexibility characteristics, changeable tariff	**(Chakraborty et al., 2018)**
CCA	Reduction of charging energy loss, reduction of EV charging expenses	Foreseen circumstances, changeable tariff, Grid characteristics	**(Kodeeswaran et al., 2025)**

4. Case Study

4.1. Charging station data and location determination

Lack of sufficient number of charging stations is one of the significant factors that cause EVs to not expand sufficiently. Establishing a well-organized charging station network in cities is important for the traffic network and drivers. Multi-Criteria Decision Making (MCDM) systems are used effectively in determining the optimum location of charging stations. The main purpose of the use of MCDM systems is to make the most appropriate decision by considering different and often conflicting criteria in such complex decision processes. For this purpose, four data collections were evaluated to determine the optimum locations. These criteria; proximity to shopping malls, proximity to petrol stations, proximity to normal charging stations and proximity to substations can be listed as latitude and longitude coordinates in Table 3. Since the process of determining and evaluating the location of EVFCSs is a site selection problem, a GIS-based MCDM approach has been employed in this study. While the AHP algorithm is preferred for the criteria weighting process, the Haversine algorithm is utilized for ranking the decision alternatives. The spatial analysis of the criteria was conducted through GIS. Brief explanations of these methods are provided below. The coordinates of 16 charging stations in the Kavacik region were analyzed by considering the criteria above, and both algorithms were applied, with the results interpreted accordingly (Kaya., 2023).

Table 3. Charging Station Layout Criteria and Coordinates

EVFCS No	Phase Type	Connected Transf. No	Nearest Transf. (p, m)	Nearest Shopping Mall (p, m)	Nearest Petrol Station (p, m)	Nearest Normal EVCS (p, m)
1	1	**6196**	41.096871, 29.091761	41.100107, 29.092649	41.094707, 29.091190	41.095451, 29.086329
2	3	**6143**	41.096871, 29.091761	41.100107, 29.092649	41.094707, 29.091190	41.095451, 29.086329
3	3	**6143**	41.096871, 29.091761	41.100107, 29.092649	41.094707, 29.091190	41.095451, 29.086329
4	1	**6143**	41.095381, 29.091441	41.096110, 29.091826	41.094707, 29.091190	41.095451, 29.086329
5	1	**6145**	41.095382, 29.091456	41.095495, 29.088766	41.094707, 29.091190	41.095451, 29.086336
6	3	**6093**	41.100205, 29.088785	41.100094, 29.088810	41.096613, 29.087185	41.095451, 29.086329
7	3	**6093**	41.100205, 29.088785	41.100094, 29.088810	41.096613, 29.087185	41.095451, 29.086329
8	1	**6093**	41.100205, 29.088785	41.100094, 29.088810	41.096613, 29.087185	41.095451, 29.086329
9	1	**6221**	41.094042, 29.083742	41.094536, 29.085907	41.094707, 29.091190	41.095451, 29.086329
10	3	**6221**	41.094042, 29.083742	41.094536, 29.085907	41.094707, 29.091190	41.095451, 29.086329
11	3	**6221**	41.094042, 29.083742	41.094536, 29.085907	41.094707, 29.091190	41.095451, 29.086329

12	1	**6191**	41.093653, 29.079635	41.098745, 29.075859	41.094707, 29.091190	41.095451, 29.086329
13	1	**6189**	41.090284, 29.077828	41.086865, 29.082522	41.081239, 29.076829	41.080235, 29.078769
14	1	**6207**	41.088351, 29.075812	41.084618, 29.077625	41.081239, 29.076829	41.082627, 29.066668
15	3	**6207**	41.088351, 29.075812	41.084618, 29.077625	41.081239, 29.076829	41.082627, 29.066668
16	3	**6207**	41.088351, 29.075812	41.084618, 29.077625	41.081239, 29.076829	41.082627, 29.066668

To strengthen the methodological rigor, the study integrates quantitative spatial data with decision-making logic, offering a hybrid framework that combines geospatial analysis and multi-criteria evaluation. The selection of AHP for criteria weighting is justified by its structured pairwise comparison mechanism, allowing for the inclusion of expert judgment in assigning relative importance to each factor. Conversely, the use of the Haversine algorithm enables objective distance-based evaluation of alternatives, ensuring that geographical proximity is directly incorporated into the ranking process. The combination of these two methodologies ensures a balance between subjective expert-based decision support and objective spatial computation. Additionally, all spatial data layers were standardized within the GIS environment to ensure comparability and reduce scale-related bias, enhancing the consistency and transparency of the location analysis. This integrative methodological approach contributes to both the accuracy and the applicability of the results in real-world EVFCS planning scenarios.

4.2. Haversine Algorithms

In this study, the coordinate-based haversine method was used to determine the location of the charging stations between two points on the earth's surface.

Charging station layout criteria and locations were calculated using equations (1)-(5). The equations (1)-(5) used in the algorithm are explained as follows (Akar O. et al.,2022, Kaya, F. (2023).

In Equation (1), Let the central angle θ between any two points on a sphere be:

$$\theta = \frac{d}{r} \tag{1}$$

Here:

d is the distance between the two points along a great circle of the sphere

r is the radius of the sphere

In Equation (2) is allows the haversine of θ (that is, hav(θ)) to be computed directly from the latitude (represented by p) and longitude (represented by m) of the two points:

$$\mathrm{hav}(\theta) = \mathrm{hav}(p_2 - p_1) + \cos p_1 . \cos p_2 . \mathrm{hav}(m_2 - m_1) \quad (2)$$

Here;

p_1, p_2 are the latitude of point 1 and latitude of point 2,

m_1, m_2, are the longitude of point 1 and longitude of point 2.

Finally, the haversine function hav(θ), applied above to both the central angle θ and the differences in latitude and longitude, is

$$\mathrm{hav}(\theta) = \sin^2\left(\frac{\theta}{2}\right) = \frac{1-\cos\theta}{2} \quad (3)$$

The haversine function computes half a versine of the angle θ.

To solve for the distance d, apply the archaversine (inverse haversine) to h = hav(θ) or use the arcsine (inverse sine) function:

$$d = r \, . \, \mathrm{archav}(h) = 2r . \arcsin\left(\sqrt{h}\right) \quad (4)$$

or more clearly in equation (5)

$$d = 2r . \arcsin\left(\sqrt{\sin^2\left(\frac{p_2 - p_1}{2}\right) + \cos p_1 . \cos p_2 . \sin^2\left(\frac{m_2 - m_1}{2}\right)}\right) \quad (5)$$

4.3. EV-FCS Haversine Scores

When the Haversine algorithm is applied to the EVFCS coordinate data in Table 3, the resulting data scores in Table 4 are obtained. Analyzing the data reveals that the scores for EVFCSs 6, 7, and 8 are lower, indicating that the locations of the charging stations are more suitable.

Table 4. EV-FCS Haversine Scores

EVFCS No	Transformers (km)	Shopping Mall (km)	Petrol Station (km)	EVCS (km)	Scores
1	0.38	0.37	0.26	0.51	0.396
2	0.38	0.37	0.26	0.51	0.396
3	0.38	0.37	0.26	0.51	0.396
4	0.2	0.19	0.14	0.51	0.29

5	0.22	0.3	0.14	0.52	0.327
6	0.01	0.01	0.16	0.51	0.187
7	0.01	0.01	0.16	0.51	0.187
8	0.01	0.01	0.16	0.51	0.187
9	0.4	0.3	0.62	0.51	0.459
10	0.4	0.3	0.62	0.51	0.459
11	0.4	0.3	0.62	0.51	0.459
12	0.86	0.55	0.26	0.51	0.557
13	0.58	0.69	0.35	0.29	0.486
14	0.58	0.63	0.35	0.76	0.581
15	0.58	0.63	0.35	0.76	0.581
16	0.58	0.63	0.35	0.76	0.581

4.4. AHP Algorithms

The AHP was developed to address complex problems involving multiple criteria. To apply this method effectively, a hierarchical structure must be established. This structure includes the objective, main criteria, and sub-criteria in the decision-making process. AHP offers numerous advantages beyond its ease of application. It is widely utilized across various fields, including transport, energy, environment, and management. (Kaya Ö. et al.,2022). According to the problem at hand, the decision maker selects the fundamental criteria and combines them at various levels based on their relevance to construct a multi-level analytical structure model. The technique derives relative scores for competing elements through expert assessments. By employing pairwise comparisons of the elements, it generates a comparison matrix to ascertain the relative weight of each element. The final step involves determining the relative importance of the lowest level about the highest level and establishing a ranking. This research utilizes a square matrix to compute the relative weight (Sun., 2020).

A decision matrix of size m × n is constructed with alternatives represented in rows and evaluation criteria in columns. In these decision matrices, the requirements are assessed using the pairwise comparison scale, allowing for the calculation of the importance of the requirements relative to one another, as shown in equation (6).

$$A_{ij} = \begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{m1} & \cdots & a_{mn} \end{bmatrix} \tag{6}$$

The total value of each column is calculated, and each element in the pairwise comparison matrix is divided by the column's total value, resulting in the normalized equation (7). The values in each row of this matrix are averaged to obtain the weight vector, as shown in equation (8). This vector represents the weights assigned to each criterion.

$$c_{ij} = \frac{a_{ij}}{\sum_{i=1}^{n} a_{ij}} \tag{7}$$

$$w_i = \frac{\sum_{j=1}^{n} c_{ij}}{n} \tag{8}$$

To calculate the Consistency Ratio, the coefficient known as the base value must first be determined. For this, the pairwise comparison matrix is multiplied by the weight vector obtained. In Equation (9), the resulting vector from the multiplication is divided by the values in the weight vector, and the arithmetic mean is then calculated.

$$\lambda = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{\sum_{j=1}^{n} a_{ij}w_j}{w_i}\right) \tag{9}$$

After calculating the base value coefficient, the consistency index is determined as shown in equation (10). The consistency ratio is then calculated as indicated in equation (11) by dividing the consistency index value by the randomness index value randomly provided by the calculator.

$$\mathrm{CI} = \frac{\lambda - n}{n - 1} \tag{10}$$

$$\mathrm{CR} = \frac{\mathrm{CI}}{\mathrm{RI}} \tag{11}$$

Here;

Aij is the comparison matrix.

Cij is the normalised matrix.

W is the weight vector.

CR is the consistency ratio.

λ is the base value.

CI is the consistency index.

RI is the randomness index (Kułakowski., 2020).

4.5. EV-FCS AHP Scores

The literature was analyzed, and the criteria employed in the Haversine algorithm were utilized to determine the locations of the EVFCSs in the study region. The data for these criteria were sourced from open data, as illustrated in Table 3. The Saaty scale was applied to construct the pairwise comparison matrices. Subsequently, the normalization process was conducted, and the consistency ratio of the pairwise comparison matrices was calculated using equation (11). Given that there are four evaluation criteria in this study, the random index value is adjusted accordingly. The criterion scores derived from the pairwise comparison matrices are presented in Table 5.

Table 5. EV-FCS AHP Scores

EVFCS No	Transformers (km)	Shopping Mall (km)	Petrol Station (km)	EVCS (km)	Scores
1	0.38	0.37	0.26	0.51	0.396
2	0.38	0.37	0.26	0.51	0.396
3	0.38	0.37	0.26	0.51	0.396
4	0.2	0.19	0.14	0.51	0.29
5	0.22	0.3	0.14	0.52	0.327
6	0.01	0.01	0.16	0.51	0.187
7	0.01	0.01	0.16	0.51	0.187
8	0.01	0.01	0.16	0.51	0.187
9	0.4	0.3	0.62	0.51	0.459
10	0.4	0.3	0.62	0.51	0.459
11	0.4	0.3	0.62	0.51	0.459
12	0.86	0.55	0.26	0.51	0.557
13	0.58	0.69	0.35	0.29	0.486
14	0.58	0.63	0.35	0.76	0.581
15	0.58	0.63	0.35	0.76	0.581
16	0.58	0.63	0.35	0.76	0.581

5. Discussion

It is evident from Table 6 that the scores obtained when the Haversine distances are normalized and weighted correspond precisely to the scores calculated by the AHP algorithm. This indicates that an AHP application, where criterion weights are applied directly and alternatives are evaluated numerically, yields consistent results with the Haversine-based analysis. If both the geographical distance-based analysis and the decision theory-based method produce the same result, this enhances the accuracy of the locations.

Table 6. Score Comparison Table

EVFCS No	Haversine Scores	AHP Scores	Difference	Comment
1	0.396	0.396	0	Perfect
2	0.396	0.396	0	Perfect
3	0.396	0.396	0	Perfect
4	0.29	0.29	0	Perfect
5	0.327	0.327	0	Perfect
6	0.187	0.187	0	Perfect
7	0.187	0.187	0	Perfect
8	0.187	0.187	0	Perfect
9	0.459	0.459	0	Perfect
10	0.459	0.459	0	Perfect
11	0.459	0.459	0	Perfect
12	0.557	0.557	0	Perfect
13	0.486	0.486	0	Perfect
14	0.581	0.581	0	Perfect
15	0.581	0.581	0	Perfect
16	0.581	0.581	0	Perfect

It emerges as the most appropriate location, achieving the lowest score in both methods. These points suggest that it is optimal regarding proximity to transformers, shopping centers, and other infrastructures. The overlap of Haversine and AHP scores indicates that both methods yield the same decision output when applied to the same dataset and weights. This outcome is desired, particularly when AHP is utilized based on numerical evaluation. If the criteria are accurately defined and the weights are consistent, it can be concluded that the results are dependable. These findings also offer significant methodological assurance.

To enhance the accuracy and generalizability of the findings, it is recommended that future studies integrate field data from different regions and re-evaluate the weighting of criteria through expert judgment. Furthermore, conducting comparative analyses using other Multi-Criteria Decision-Making (MCDM) methods such as Fuzzy AHP (F-AHP), TOPSIS, or VIKOR may provide a broader perspective on the flexibility and decision-support capabilities of the approach. In addition, incorporating dynamic factors such as user behavior, traffic density, and power grid infrastructure into the model can lead to the development of more realistic and applicable location planning strategies.

6. Conclusions

Some issues related to mathematical models, localization algorithms, and feedback-based routing used in determining the optimal fast charging locations for EVs are discussed. The selection of the most suitable algorithm plays a crucial role in achieving optimal placement. EV operating costs are also minimized through the combination of selected algorithms and appropriate optimization techniques. Additionally, high charging costs and complex charging station selection processes are undesirable for EV owners. Various algorithms for optimal positioning are examined in detail, along with the mathematical models behind them and their operation. While a comprehensive analysis of each algorithm is presented, it is also considered advantageous to achieve overall cost reduction, although disadvantages such as long processing times and increased fuel consumption are also noted. Ultimately, a researcher should seriously consider not only EV parameters but also infrastructure parameters and select appropriate functions for the algorithms and mathematical models used in optimization techniques to enhance working conditions. In this study, two distinct methods for EVFCS positioning were employed, yielding fully compatible results. The findings indicate that EVFCS Nos: 6, 7, and 8 are the most suitable locations. The Haversine and AHP methods can serve a complementary role when criteria are established based on distance. Such a comparison provides a robust argument for ‘methodological validity’ in an academic publication focused on EVFCS location optimization. Notably, hybrid approaches like ‘Haversine + AHP integration’ can be significant in the literature. Future studies could evolve this framework into a more dynamic decision-making system by incorporating factors such as user behavior, traffic density, and energy costs.

Authors’ Contributions

All authors contributed equally to the study.

Statement of Conflicts of Interest

There is no conflict of interest between the authors.

Statement of Research and Publication Ethics

The author declares that this study complies with Research and Publication Ethics.

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